The Return on Information Technology: Who Benefits Most?

E. Dhyne[1], J. Konings[2], J. Van den bosch[3] & S. Vanormelingen[4]

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Abstract: This paper uses a new microdata set of B2B firm-level transactions in Belgium to construct a measure of ICT investment at the firm level, which we combine with the income statement of firms to analyze the impact of ICT on productivity. We find that a firm investing an additional euro in ICT increases value added by 1 euro and 35 cents on average. This marginal product of ICT investment increases with firm size and varies across sectors. While we find substantial returns of ICT at the firm level, such returns are much lower at the aggregate level. This is due to underinvestment in ICT (ICT capital deepening is low) and misallocation of ICT investments.

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[1] National Bank of Belgium and University of Mons, Boulevard de Berlaimont 14, B-1000 Bruxelles. *E-mail*: Emmanuel.dhyne@nbb.be

[2] University of Liverpool Management School; KU Leuven and CEPR, Naamsestraat 69, 3000 Leuven. *E-mail:* joep.konings@kuleuven.be

[3] KU Leuven and IMEC, Naamsestraat 69, 3000 Leuven, Belgium. *E-mail :* jeroen.vandenbosch@kuleuven.be

[4] KU Leuven, Warmoesberg 26, 1000 Brussels, Belgium. *E-mail :* stijn.vanormelingen@kuleuven.be

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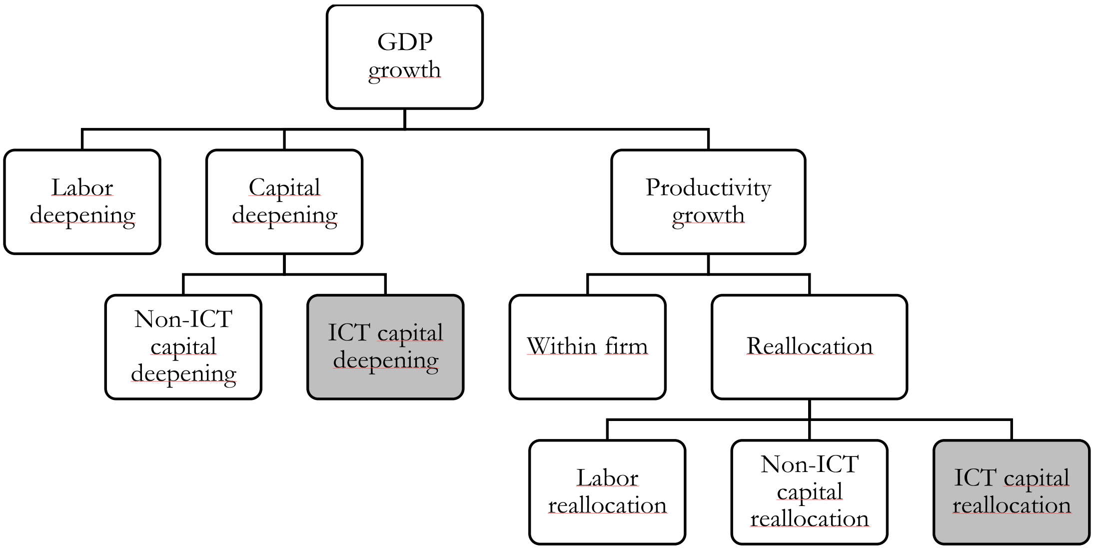
1. Introduction

The financial crisis of 2008 triggered a collapse in productivity growth, which has not caught up with its long run trend since then. This seems at odds with the increased spread of information technology, artificial intelligence, and automation of the last couple of decades. This productivity puzzle has been widespread in OECD countries and more recently also in emerging economies (Syverson, 2017). It seems that the Solow (1987) paradox, which refers to the disconnect between observed productivity statistics and the emergence of information technology, is more relevant than ever.

This paper investigates heterogeneity in the returns on ICT across firms, industries, and time and analyzes how granular (firm-level) channels affect the aggregate productivity numbers. We decompose aggregate GDP growth into various micro channels to understand where the relatively low aggregate returns on ICT emerge from, which is illustrated in Figure 1. In particular, GDP in a country can increase by using more production factors, such as labor or capital. We distinguish between ICT and non-ICT capital investments and investigate their return. Figure 1 also shows that GDP growth can occur due to productivity growth, which means that a country produces more goods with the same amount of labor and capital and hence it is producing more efficiently. Such productivity growth can also happen when resources are allocated to its most productive use, this is what we call the reallocation effect. In this case, ICT capital contributes to aggregate productivity growth when it is invested in firms that benefit most from ICT.

FIGURE 1: DECOMPOSING GDP GROWTH



We use a new and comprehensive microdata set of B2B firm-level transactions in Belgium to construct a measure of ICT investments at the firm level, which we trace between 2002 and 2013. Our measure of ICT includes *all* domestic purchases and imports from ICT suppliers, which is an improvement to earlier research, mainly based on survey data of mostly large firms. Hence these tend to miss a large fraction of investments and firm heterogeneity (Brynjolfsson and Yang, 1996; Dedrick, Gurbaxani and Kraemer, 2003). Furthermore, most of the literature identifies ICT as broad investments in office and computing equipment and therefore does not capture precisely the extent of technological change, which may also be induced by software and communications technology, especially in the last two decades.

We combine this newly constructed panel data on ICT investments with financial and operational information from the income statements of firms, which allows us to estimate the impact of ICT on firm level productivity. To this end, we use a control function approach to estimate the output elasticity and marginal product of ICT capital. This approach deals with biases in estimating production functions related to the simultaneity of input and output decisions, measurement errors, and omitted variables (Brynjolfsson and Hitt, 1995; Hempell, 2002; Cardona, Kretschmer and Strobel, 2013). Another advantage of our data is that it covers all incorporated firms in the Belgian economy. Earlier work did not have access to such comprehensive data, which makes it harder to draw inferences about the impact of ICT on *aggregate* productivity growth (Hitt and Brynjolfsson, 2000). We also exploit the cross section and time dimension of our panel data set and show the return on ICT across industries and time. The wide coverage of our data set enables us to contribute to the scarce evidence on differences in returns on ICT depending on the size of the firm (Bloom, Draca, Kretschmer, Sadun, and Van Reenen, 2010; Tambe and Hitt, 2012). By exploiting information about the identity of the ICT supplier, we are able to split ICT purchases into IT goods, IT services, communication goods, and communication services. We relate heterogeneity in the composition of ICT capital to reconcile the heterogeneity in returns on ICT across industries and the firm size distribution.

We confirm earlier findings that ICT capital effectively contributes to output and more importantly that there exist excess returns on ICT since ICT investment costs are lower than their gross returns. This effect is not only confined to the ICT producing industries, but also to the ICT using industries. We find that large firms benefit more from ICT than small firms. This finding is not caused by differences in the composition of ICT capital and it is robust to adding firm fixed effects, controlling for labor quality, decentralization, and management practices. To see whether these findings can be reconciled with the limited impact of ICT at the aggregate level, we compute aggregate productivity growth from our micro-level data set and use the decomposition introduced by Petrin and Levinsohn (2012), as summarized in Figure 1. Our results indicate that part of the observed productivity puzzle can be explained by two causes: (i) low ICT investments, especially by large firms, and (ii) misallocation of ICT investments. We find these effects to be particularly apparent after the Great Recession.

The rest of the paper is organized as follows. The next section summarizes the relevant literature. Section 3 discusses the various data sets used to construct ICT capital. Section 4 explains the econometric model and the control function approach that we use to estimate productivity, taking into account that ICT investment is an endogenous choice by the firm. Section 5 discusses the results and section 6 concludes.

2. Literature Review

Early research by Roach (1987) and Solow (1987) concluded that ICT appeared everywhere, but in the productivity statistics. This so called 'productivity paradox' was resolved in various firm level studies, amongst others by Brynjolfsson (1993), Lichtenberg (1995), Brynjolfsson and Hitt (1996), Aral, Brynjolfsson and Wu (2006), Mithas, Tafti, Bardhan and Goh (2012) and Aral, Brynjolfsson and Van Alstyne (2012). Review papers on the literature by Brynjolfsson and Hitt (2000), Melville, Kraemer and Gurbaxani (2004), Cardona, Kretschmer and Strobel (2013) and Biagi (2013) conclude that ICT has a positive effect on productivity, albeit with large heterogeneity in estimated returns on ICT across studies.

Several factors explain the large heterogeneity in estimated returns on ICT. The research design of studies explains about 35% of the variation in empirical estimates of ICT elasticities (Stiroh, 2005). In particular, Sabherwal and Jeyaraj (2015) found that the return on ICT is estimated higher when primary data sources are used and sample sizes are larger. Kohli and Devaraj (2003) suggest to focus on gathering large panel data sets from primary sources and using productivity-based dependent variables to assess the payoff from ICT. The introduction of such a framework to evaluate the return on ICT is an important contribution of this paper.

Another challenge in ICT studies is related to measurement. Firms are typically not required to report ICT investments separately from other capital investments. Furthermore, ICT investments often require large complementary investments in the reorganization of work practices or the development of new business processes and worker skills. Brynjolfsson and Yang (1997) find that up to nine-tenths of the costs of computer capital are embodied in intangible assets. Bharadwaj (2000), Black and Lynch (2001), Breshnahan, Brynjolfsson and Hitt (2002) and Aral and Weill (2007) show that alignment between ICT investments and complementary workplace organization practices are important to realize profit and productivity gains from ICT. It is thus important to capture the complete extent of the ICT investment, which is typically not confined to hardware expenditures. To this end, this paper proposes a comprehensive ICT investment measure that captures both ICT goods and ICT services.

Due to the unavailability of ICT investment data in financial statements of firms, researchers are often restricted to survey data of selected samples of large firms.[5] This results in a selection bias in many firm level studies and a lack of insights on heterogeneity in returns on ICT across countries, industries and the firm size distribution (Tam, 1998). Van Reenen, Bloom, Draca, Kretschmer and Sadun (2010) find no evidence of a size premium in returns on ICT while Tambe and Hitt (2012) find that large firms benefit more from ICT. Note however that "small" firms in these samples are still relatively large. For example, a small firm in Tambe and Hitt (2012) is a non-Fortune 500 firm with an average value added of over $500 million. In our data we cover the full range of the size distribution, including micro firms.

While adequate data for estimating productivity is available in the financial statements of firms, there are various endogeneity issues that need to be accounted for to obtain unbiased estimates of ICT elasticities, see Stiroh (2005), Van Biesebroeck (2007) and Van Beveren (2012). State of the art techniques to do so require relatively large panel data sets. This is probably why such methods are not frequently used in ICT studies. The only studies that do so are Van Reenen et al. (2010) and Bloom, Sadun and Van Reenen (2012), who rely on the Olley and Pakes (1996) estimation procedure to obtain unbiased production function coefficients. This paper introduces more novel semiparametric estimation techniques by Ackerberg, Caves and Frazer (2015) and Collard-Wexler and De Loecker (2016) in the ICT literature.

Studies on the macroeconomic impact of ICT typically rely on industry level data and strong assumptions such as constant returns to scale and competitive markets (Oliner and Sichel, 2000, Jorgenson, 2001, Stiroh, 2002, Jorgenson, Ho and Stiroh, 2008, van Ark, O'Mahony and Timmer, 2008). However, just like there is substantial heterogeneity within industries in firm size and productivity, there is firm heterogeneity in returns on ICT. Industry average returns on ICT hide this heterogeneity while the aggregate impact of ICT also depends on which firms are investing in ICT. This could explain why most studies find large returns on ICT at the micro level, but lower productivity gains at the macro level, especially in Europe (Van Ark, 2014). We compute aggregate growth and subsequently decompose it in its different micro level foundations using the Petrin and Levinsohn (2012) decomposition.

[5] E.g. the Computerworld magazine survey (Fortune 500 firms), InformationWeek magazine survey (top 500 IT intensive firms in the U.S.), Computer Intelligence Technology Database survey (Fortune 1000 firms) or the Harte-Hanks survey (sample of firms with more than 100 employees in Europe and U.S.).

3. Data

We combine different confidential micro data sets which were provided by the National Bank of Belgium. The first one covers a subset of B2B transactions data described in Dhyne, Magerman and Rubinova (2015). This data set is constructed from the yearly customer listing in the tax declarations of firms. In this customer listing, firms have to report the sales invoices per customer. We use the customer listing of all firms that are active in ICT producing and selling industries to calculate how much each of their customers has spent on ICT per year for the period 2002-2013. This approach is similar to Hitt, Wu and Zhou (2002), who retrieve a measure for IT investments from the customer listing of a large SAP supplier in the United States. Our data set is more comprehensive since it covers all ICT suppliers. We define ICT producers based on their four digit primary NACE sector code as shown in table 1.[6] We differentiate between IT goods, IT services, communication goods and communication services within these purchases.[7] For example, if a firm makes a purchase from a supplier that has its primary activity in sector 2620 – *Manufacture of computers and peripheral equipment* - we classify this purchase as an investment in IT goods.

TABLE 1: ICT PRODUCING INDUSTRIES

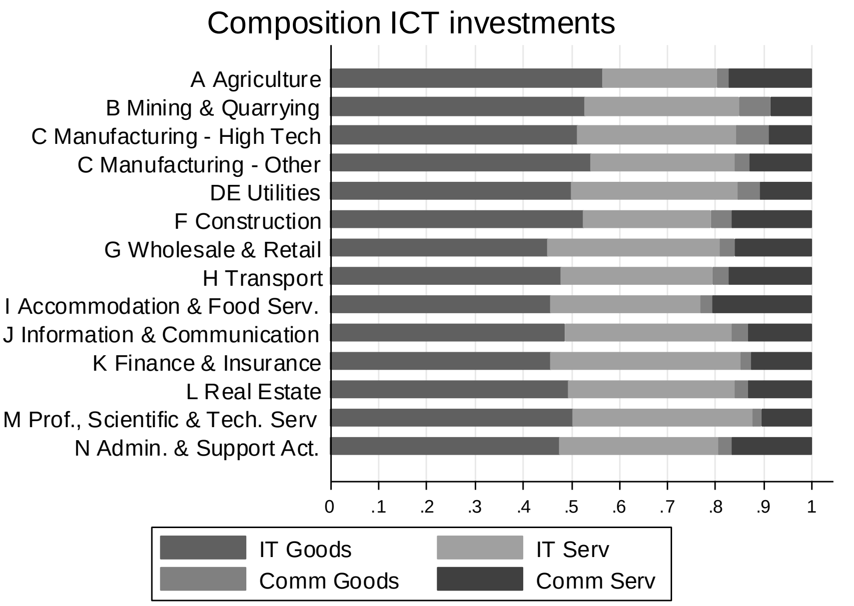
ICT type	NACE Rev 2 code	Description
IT goods	2620	Manufacture of computers and peripheral equipment
	4651	Wholesale of computers, computer peripheral equipment and software
	4741	Retail sale of computers, peripheral units and software in specialized stores
	5829	Other software publishing
IT services	6200	Computer programming, consultancy and related activities
	6201	Computer programming activities
	6202	Computer consultancy activities
	6203	Computer facilities management activities
	6209	Other information technology and computer service activities
	6311	Data processing, hosting and related activities
	6312	Web portals
Communication goods	2630	Manufacture of communication equipment
	4652	Wholesale of electronic and telecommunications equipment and parts
	4742	Retail sale of telecommunications equipment in specialized stores
Communication services	6110	Wired telecommunications activities
	6120	Wireless telecommunications activities
	6130	Satellite telecommunications activities
	6190	Other telecommunications activities

[6] Earlier studies used more aggregate - mostly two-digit, sometimes three-digit - definitions of ICT producing industries and thus contain more noise. For example, Houseman et al. (2015) and Acemoglu et al. (2014) use data from the NAICS 334 industry, which also includes manufacturing of audio and video equipment, navigational measuring, electro-medical and control instruments and magnetic and optical media.

[7] We have no information on whether the purchase is tangible or intangible. Also, a breakdown which shows how much of the ICT purchase are investments, how much are unutilized or how much are utilized intermediate inputs, is unfortunately not available. Appendix C2 discusses this further and appendix C3 includes robustness checks on this potential issue.

While the inter-firms transaction data set provides information on domestic ICT investments for all Belgian firms, it is possible in a small and open economy such as Belgium that firms import ICT. Therefore, we add import data at the product-firm level to capture ICT purchases from abroad. This data set is collected from the customs office for imports from outside the EU and the Intrastat trade survey for imports from within the EU. We merge this data set based on the detailed HS 8 digit codes. Altogether, this results in an ICT investment data set that is representative for the entire Belgian population of incorporated firms for the period 2002-2013. Figure 2 shows that in most sectors IT goods account for the largest share of ICT purchases, followed by IT services, communication services and communication goods.

FIGURE 2: COMPOSITION OF ICT INVESTMENTS BY SECTOR



Notes: Own calculations based on ICT purchases data. Industry average investment shares of firm average ICT purchases.

The third data set refers to the VAT declarations, which provide the total investments and intermediate input expenditures of the firm. By merging the investment data with the inter-firm transactions data set, we can compute ICT and non-ICT investment flows, from which we construct ICT capital stocks and non-ICT capital stocks following the Perpetual Inventory Method (PIM). Appendices C2 and C3 provide more information on the ICT purchases data, how the ICT and non-ICT capital stocks are constructed and presents ICT intensity measures to show that our ICT measure behaves as expected. Appendix D2 contains various robustness checks on the choices that we make in this process.

The fourth data set consists of the annual company accounts with detailed financial and operational information, which we use to estimate productivity at the firm level. This data also reports information on the education level of employees in the firm. All incorporated firms in Belgium are required to submit company accounts to the National Bank of Belgium. We have data for the whole private sector, excluding the financial sector for which the company accounts are not available under the same format as non-financial firms.

The final data set that we use is the annual FDI survey organized by the National Bank of Belgium, which serves as an input for the national accounts. It is a comprehensive survey of all inward and outward foreign direct investments in Belgium. Appendix C1 provides more information on how we merge all data sets together and construct the estimation sample.

Table 2 provides summary statistics of the main firm level variables that we use in our analysis. The average firm employs 10 full time equivalents in our sample, while the median firm employs 2 full time workers. Average value added is equal to 859 thousand EUR, implying labor productivity in the average firm to be around 86 thousand EUR.[8] The average non-ICT and ICT capital stock are equal to 792 thousand EUR and 75 thousand EUR respectively. This means that an employee in the average firm has around 7.5 thousand EUR ICT capital to work with. The standard deviation is high, which indicates there are large differences at the firm level in the ICT capital stock. So the aggregate picture hides a lot of firm level heterogeneity.

TABLE 2: SUMMARY STATISTICS (IN 2010 EUROS)

	mean	median	standard deviation
Value Added (X1000 €)	859	136	12,768
Non-ICT Capital (X1000 €)	792	95	22,044
ICT capital (X1000 €)	75	5	2,212
Employment	10.4	2	135
Non-ICT Investment (X1000 €)	145	17	3,506
ICT investment (X1000 €)	24	1.7	553

Notes: Summaries at the firm level, after taking averages over time per firm.

[8] All monetary values in the paper are expressed in 2010 EUR.

4. Empirical framework

In order to estimate the return on ICT, we rely on a Cobb-Douglas production function. Tambe & Hitt (2012) adapt the standard production function by distinguishing between IT labor and non-IT labor. We take a similar approach and distinguish between ICT capital and non-ICT capital. By considering ICT capital as a separate input in the production function next to non-ICT capital, we follow Brynjolfsson & Hitt (1996, 2003), Dewan & Kraemer (2000), Commander, Harrison & Menezes-Filho (2011) and Bloom et al. (2012). The log-linearized Cobb-Douglas production function looks as follows[9]:

$$y_{it} = \beta_l l_{it} + \beta_{ICT} k_{it}^{ICT} + \beta_{NICT} k_{it}^{NICT} + \omega_{it} + \epsilon_{it} \tag{1}$$

In which the i and t subscripts refer to firm and year and small letters denote logs. y_{it} refers to value added in firm i at time t. l_{it}, k_{it}^{ICT} and k_{it}^{NICT} refer respectively to labor, the ICT capital stock and the non-ICT capital stock, and ω_{it} is the firm's Total Factor Productivity (TFP) in firm i at time t. Econometricians do not observe a firm's TFP, which gives rise to a simultaneity bias (Marschak & Andrews, 1944), i.e. firms typically adjust their capital and labor inputs in function of their productivity resulting in biased output elasticities. When high productive firms invest more in ICT, the output elasticity β_{ICT} would typically be overestimated with an OLS estimation of equation (1).

To account for such endogeneity the literature puts forward several parametric and non-parametric approaches (Van Biesebroeck, 2007 and Van Beveren, 2012). In practice, the most often used solutions are firm fixed effects, first differences and semiparametric estimation. Estimating equation (1) with firm fixed effects or in first differences results in unbiased estimates of the output elasticities if firm level productivity is constant over time. However, these methods do not control for firm specific productivity shocks and can lead to a substantial downward bias in the coefficient estimates of variables that display substantial serial correlation (Griliches and Hausman, 1986). For this reason, the use of semiparametric estimators is typically preferred when sample sizes are sufficiently large. Semiparametric estimation of production

[9] Dewan and Min (1997) showed that the Cobb-Douglas production function is a good approximation of the actual underlying production function in the ICT and productivity context. They found that the Translog and CES-translog production functions yield virtually identical estimates for the ICT capital output elasticity and that the elasticities of substitution between ICT and non-ICT inputs are estimated to be very close to unity, consistent with the Cobb-Douglas model. Also Kundisch, Mittal and Nault (2014) provide theoretical and empirical justification for the use of Cobb-Douglas production functions to measure the returns of information technology.

functions was introduced by Olley and Pakes (1996) and further extended by Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2015). The idea is that firms signal their productivity, which is known to the firm but unknown to the econometrician, through other decisions like investments and material purchases. This allows to proxy for unobserved productivity with a control function. Including this control function then allows to obtain unbiased production function coefficients. In appendix B1 we discuss in more detail the approach we follow, in particular, the GMM control function approach of Ackerberg, Caves and Frazer (2015) and a novel GMM estimator recently introduced by Collard-Wexler and De Loecker (2016) that also controls for measurement error in the capital stock. In appendix D1 we add robustness checks to allow for endogenous productivity growth, alternative data generating processes and mismeasurement in the capital stocks.

Using the output elasticities, we compute the marginal product of ICT capital as in Brynjolfsson and Hitt (1996) and Tambe and Hitt (2012), which is equal to the output elasticity of ICT capital multiplied by the ratio of output to ICT capital.

$$MP_{K^{ICT}} = \frac{\partial Y}{\partial K^{ICT}} = \frac{\partial Y}{\partial K^{ICT}} \frac{K^{ICT}}{Y} \frac{Y}{K^{ICT}} = \beta_{ICT} \frac{Y}{K^{ICT}} = \frac{\beta_{ICT}}{\frac{K^{ICT}}{Y}} \tag{2}$$

We calculate the ICT capital input share for each observation and take the mean of the resulting distribution after winsorizing at the 1% level to avoid biases from outliers.

5. Results

5.1 Baseline results

Table 3 reports production function estimates for the private sector as a whole. All specifications control for industry and year fixed effects. The first column shows OLS results, the second and third column report results including firm fixed effects and first differences estimates respectively. Columns 5 – 6 report the results of two GMM estimators: the Ackerberg, Caves and Frazer control function estimator (ACF) and the Collard-Wexler and De Loecker approach (CWDL).[10] For table 3, we limit the estimation sample to the firms that we have sufficient information on to use in each estimator.

TABLE 3: RESULTS PRIVATE SECTOR (NACE 1-82)

Value Added Prod. Function	OLS	Firm Fixed Effects	First differences	ACF	CWDL
Labor	0.6739***	0.5013***	0.3376***	0.6226***	0.4573****
	(0.0015)	(0.0021)	(0.0022)	(0.0038)	(0.0058)
Non-ICT Capital	0.1846***	0.1170***	0.0902***	0.2111***	0.4467***
	(0.0013)	(0.0015)	(0.0016)	(0.0055)	(0.0286)
ICT Capital	0.1079***	0.0695***	0.0599***	0.1151***	0.1387***
	(0.0009)	(0.0010)	(0.0011)	(0.0032)	(0.0313)
# observations	1,044,353	1,044,353	870,626	867,867	826,685
# firms	137,504	137,504	137,504	137,504	137,504
Ind. & Year FE	YES	/	/	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level. The estimation sample is identical in number of firms. The number of observations is lower due to missing lags/instruments for some observations in one/multiple years for a firm in the First differences, ACF and CWDL estimator.

Similar to Brynjolfsson and Hitt (1995), we observe that the magnitude of the ICT capital output elasticity drops roughly 50% when adding firm fixed effects or estimating first differences. Cross sectional firm heterogeneity is thus important in explaining the return on ICT capital. This is consistent with the idea that differences in ICT capital also reflect other unobserved persistent firm characteristics like innovativeness, management practices and workplace organization (Bresnahan, Brynjolfsson and Hitt, 2002). Another explanation is provided by Griliches and Hausman (1986) who note that when a variable is highly serially correlated over time, fixed effects regressions can introduce a substantial downward bias in the coefficient estimates. The GMM estimators in columns 5-6 are expected to control for these biases. The ACF estimator controls for the potential endogeneity of inputs, most relevant for a variable input like labor. As expected the coefficient on labor drops. The ICT capital coefficient is comparable to the OLS one. Note that it is difficult to determine a priori the bias in the OLS estimate for the ICT capital coefficient. First, there can

[10] We also experimented with the system GMM approach (Blundell and Bond, 1999). The point estimates for this estimator are similar to the OLS and control function estimates.

be an endogeneity bias if ICT is correlated with unobserved productivity, but second, the estimate is also affected by biases in other variables' coefficients that spill over to the ICT capital coefficient. As expected, correcting for measurement error in the capital stocks with the CWDL estimator in column 6 increases the capital coefficients.[11] For the remainder of this paper, we proceed with the ACF estimator as this is the workhorse model in the productivity literature. The ICT capital output elasticity is estimated around 0.11, so increasing the ICT capital stock with 1% increases value added on average with 0.11%.[12] This is higher than in earlier work, see table A-1 in appendix A for a comparison with earlier studies.

While output elasticities have the advantage of being independent of the units in which outputs and inputs are measured, they cannot be easily compared with studies on other samples that have different average levels of ICT investments or other factor input shares. Therefore, we follow Tambe and Hitt (2012) and Brynjolfsson et al. (1996) and compute the marginal product of the inputs. The ICT capital input share $\frac{K^{ICT}}{VA}$ is on average 8.53% of value added, comparable to Brynjolfsson et al. (1995) who found an input share of 9.35% for IT capital and IT labor together. Based on the estimated output elasticities of ICT capital, the marginal product of ICT capital is 1.35, or $MP_{K^{ICT}} = \beta_{ICT}\left(\frac{K^{ICT}}{Y}\right)^{-1} = \frac{0.1151}{0.0853} = 1.35$. Thus, investing an additional euro in ICT capital increases value added on average by one euro and 35 cents. For non-ICT capital and labor, the input shares are respectively 1.17 and 0.63, so the marginal product of non-ICT capital is 0.18 EUR ($MP_{K^{NICT}} = \frac{0.2111}{1.1659} = 0.18$ EUR) and the marginal product of labor is 0.99 EUR ($MP_{\mathrm{L}} = \frac{0.6226}{0.6291} = 0.99$ EUR).[13] Our estimates are higher than those of Brynjolfsson et al. (1996), who found the marginal product of IT capital to be 0.81 for a sample of 1,121 large US firms. The marginal product tells us how much the last dollar of ICT capital contributes to value added. Infra-marginal investments generally have a higher rate of return, so our results indicate that the average return on investing in ICT capital is even higher than 1.35 EUR. However, the net rate of return of ICT capital also depends on the user costs that are

[11] The ICT capital coefficient estimate of the CWDL approach is significantly higher than the estimate of the ACF approach $(z = 4; p < 0.05)$.
[12] Or a 10% increase in ICT capital multiplies value added with $e^{0.1151*\ln(1.1)} \approx 1.011$. So a 10% increase in ICT capital increases value added by 1.1%
[13] This is the marginal product of labor, which is based on the wage bill input share and represents the increase in value added from spending an additional euro on labor. MP_{L} can also be calculated as the increase in value added from adding a full time equivalent worker. The input share is then 0.00002 and $MP_L = \frac{0.6226}{0.00002} \approx 31{,}000$. So hiring an additional full time equivalent worker for a year increases value added on average by 31,000 EUR.

associated with maintaining ICT capital and the associated large adjustment costs that have to be covered when investing in ICT (Stiroh, 2005).[14] According to EU KLEMS data ICT capital depreciates at a rate of 31.5% per year. Non-ICT capital depreciation rates are lower and estimated between 5% and 15% per year. As a result, the net rate of return on ICT capital is about $1.35 - 0.315 \approx 1.04$ while the net rate of return of non-ICT capital is about $0.18 - 0.10 \approx 0.08$. Table 4 shows that our results are robust to various alternative modeling approaches.

TABLE 4: ROBUSTNESS CHECKS

Robustness check	Potential concern	Robustness analysis	Results
R. 1	Entry and exit dynamics could affect the ICT output elasticity	Estimate the production function on a balanced sample.	✓
R. 2	Productivity could evolve endogenously with ICT investments	Include ICT investments in the law of motion of productivity.	✓
R. 3	Timing assumptions on the moment ICT investments become productive	Use current/lagged instruments for ICT capital.	✓
R. 4	ICT capital stock can be constructed in various ways	Estimate initial capital stocks from aggregated ICT intensity measures.	✓
R. 5	Sensitivities in ICT investments could spill over to non-ICT investments	ICT capital with PIM, non-ICT capital as residual book value of tangible fixed assets / as total book value of tangible fixed assets.	✓
R. 6	High ICT purchases compared to total investments	Drop observations for which ICT purchases are larger than total investments.	✓
R. 7	ICT capital depreciation rate could be too conservative	Assume no depreciation for ICT capital.	✓

Notes: The results of these robustness checks are included in appendix D.

Altogether, our results indicate excess returns on ICT capital. While part of this return on ICT is required to cover adjustment costs and unmeasured complementary assets, an increase in ICT capital would result in increased output and growth in (measured) multifactor productivity. This finding is of course not new, see Biagi (2013) for an overview of the literature on ICT and productivity. Yet, it is valuable to assess the return on ICT outside the United States with recent, more detailed data and robust estimators. More importantly, these baseline results hide a lot of heterogeneity as shown in figure A-1 in appendix A. In the remainder of the paper, we disentangle the return on ICT across industries, firm size and time. We also show how aggregate output and productivity growth is affected by ICT using a decomposition exercise.

[14] The marginal product of an input is interpreted as its gross rate of return, whereas the net rate of return is defined as the difference between the marginal product and the depreciation rate, as in Hall, Mairesse and Mohnen (2009).

5.2 Industry Heterogeneity

As pointed out by Tambe and Hitt (2012), limited availability of data in earlier work did not allow to engage in sectoral comparisons. Our data contains information on firm-level ICT investments for the entire non-financial private sector. Table 5 shows split sample results for manufacturing and services sectors as a first step in disentangling this heterogeneity.

TABLE 5: RESULTS MANUFACTURING (NACE 10-33) AND SERVICES (NACE 45-82)

Value Added Production Function	Manufacturing	Services
Labor	0.6509***	0.6153***
	(0.0124)	(0.0046)
Non-ICT Capital	0.2249***	0.1995***
	(0.0148)	(0.0071)
ICT Capital	0.1212***	0.1204***
	(0.0071)	(0.0046)
# observations	122,415	570,484
# firms	18,451	112,263
Industry & Year FE	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level. Results obtained from the ACF estimator. Tables A-3 and A-4 in appendix A show results for alternative estimators.

As in Kudyba and Diwan (2002), we find that the output elasticity of ICT capital in the manufacturing and services sector are very similar. However, the manufacturing industries have lower ICT intensity than the services industries, as measured by the ratio of ICT capital to value added. As a result, the marginal product of ICT capital is higher for manufacturing industries, in particular, 1.58 in the manufacturing sector compared to 1.17 in the services sector. The marginal products of non-ICT capital and labor are respectively 0.21 and 0.94 for the manufacturing sector and 0.16 and 1.00 for the services sector.[15] There are two possible explanations for such a high marginal product of ICT capital in the manufacturing industry: either user costs and adjustment costs from increasing ICT capital are large such that firms refrain from investing in ICT capital, or there is a market failure that results in manufacturing firms underinvesting in ICT capital. To gain a deeper understanding in industry heterogeneity, we estimate our production function at a more disaggregated level. Table 6 and table A-6 in appendix A provide further details on differences in the output elasticity and the marginal product of ICT capital across industries.

[15] For manufacturing, $MP_{K^{ICT}} = \frac{0.1212}{0.0769} = 1.58$; $MP_{K^{NICT}} = \frac{0.2249}{1.0749} = 0.21$; $MP_L = \frac{0.6509}{0.6908} = 0.94$ and for services $MP_{K^{ICT}} = \frac{0.1204}{0.1029} = 1.17$; $MP_{K^{NICT}} = \frac{0.1995}{1.2185} = 0.16$; $MP_L = \frac{0.6153}{0.6175} = 1.00$. When computing MP_L based on the number of full time equivalents, $MP_L = \frac{0.6509}{0.00002} = 32{,}690$ for manufacturing, and $MP_L = \frac{0.6153}{0.00002} = 30{,}645$ for services.

TABLE 6: RESULTS PER INDUSTRY[16]

Industry (NACE codes)	# firms	Labor	Non-ICT Capital	ICT Capital	ICT input share	Marginal Product ICT
Agriculture, Forestry and Fishing (1-3)	2,230	0.43	0.41	0.06	0.03	1.89
High Tech Manuf. (21; 26; 30)	2,509	0.73	0.16	0.15	0.09	1.65
Other Manuf. (10-33 except High Tech)	15,942	0.64	0.24	0.11	0.07	1.52
Utilities (35-39)	823	0.55	0.31	0.09	0.04	2.43
Construction (41-43)	30,751	0.64	0.24	0.09	0.04	2.38
Wholesale and Retail (45-47)	51,914	0.60	0.19	0.15	0.10	1.45
Transportation and Storage (49-53)	8,386	0.65	0.23	0.07	0.04	1.85
Accommodation and food serv. (53-56)	18,025	0.60	0.25	0.06	0.05	1.16
Information and Communication (58-63)	1,389	0.64	0.15	0.19	0.21	0.93
Financial and Insurance (64-66)	2,217	0.68	0.18	0.12	0.14	0.86
Real Estate (68)	3,602	0.50	0.34	0.12	0.14	0.83
Prof., Scientific & Tech. activities (69-75)	18,147	0.63	0.15	0.13	0.17	0.77
Admin. and Support activities (77-82)	8,583	0.64	0.23	0.12	0.13	0.96

Notes: Results obtained from the ACF estimator. The production functions include industry and year fixed effects. Standard errors are clustered at the firm level. All output elasticities are significant at the 1% level, except for utilities industries where results are significant at the 10% level. The number of observations for mining and quarrying firms is low, therefore these are omitted.

In the manufacturing sector, spending an additional euro on ICT has a larger gross return in high tech industries. The difference between high tech and other manufacturing is primarily driven by a higher output elasticity of ICT capital in high tech industries, while the ICT input shares do not differ much between high tech manufacturing and other manufacturing. Table A-6 in appendix A estimates the return on ICT at the more disaggregated two-digit level. Within manufacturing, the gross return on ICT is lowest in the printing industry and highest in manufacturing of metal. Outside manufacturing, we find that the marginal product of ICT capital is high for utilities and construction industries and in general low in services industries due to relatively high ICT input shares. For the services industries, the output elasticity of ICT capital is highest for the Information and Communication industries. This is consistent with Bosworth and Triplett (2007), who show that productivity growth from IT capital within the services sector was highest for these industries. Yet, the ICT input share is also highest in the information and communication industries, resulting in a marginal product of ICT that is relatively low.

Abstracting from potential discrepancies in adjustment costs across industries, creating productivity growth through investments in ICT is hardest in industries that have a relatively low marginal product of ICT

[16] Table A-5 in appendix A shows the results when ICT capital is constructed solely from ICT goods. ICT services can be developed in-house. Such ICT capital is unobserved in our data and could confound industry comparisons. We find that excluding ICT services typically decreases the ICT input share more than the output elasticity, as a result the marginal product of ICT increases. The ranking of table 6 remains largely unchanged, except for some industries in which ICT services are an important part of the ICT capital stock, like the financial and insurance industries.

capital. Our results suggest that it is easier for manufacturing firms to increase productivity by investing in ICT compared to services industries. Table 6 shows that this is primarily due to relatively high ICT capital stocks compared to the added value of firms in services industries.

To improve our understanding in the heterogeneity in gross marginal returns on ICT across industries, we further exploit our B2B data. As detailed in table 1, we can classify the type of ICT investments based on the primary industry code of the ICT seller. In table 7, we regress the marginal product of ICT capital on the share of IT goods, IT services, communication goods and communication services.

TABLE 7: EXPLAINING INDUSTRY HETEROGENEITY

	MP^{ICT}	MP^{ICT}	MP^{ICT}	MP^{ICT}
Share of IT goods	0.0101* (0.0059)			
Share of IT services		-0.0146** (0.0058)		
Share of Communication goods			-0.0022 (0.0065)	
Share of Communication services				0.0094 (0.0085)
# observations	816	816	816	816
Industry & Year FE	YES	YES	YES	YES

Notes: *** is significant at 1% level. ** is significant at 5% level. * is significant at 10% level. Standard errors are clustered at the two-digit level. We have 68 two-digit industry codes for 12 years, resulting in 816 observations. The dependent variable is the log linearized marginal product of ICT capital, obtained from the two-digit output elasticities in table A-6 and the cost share of ICT averaged by two-digit and year. The independent variables are the ICT type investment shares as defined in table 1 and figure 2, rescaled between 0 and 100, also averaged by two-digit and year.

Wilson (2009) shows that the marginal product of communication goods is lower than the marginal product of hardware and software. Controlling for industry and year fixed effects, our results indicate that higher investments in communication goods and services have no statistically significant effect on the marginal product of ICT capital, which is not surprising given the small share of communication goods and services investments in total ICT investments as shown in figure 1. We find that the marginal product of ICT capital is higher (lower) in industries where firms allocate more of their ICT investments to IT goods (services). With regard to realizing productivity growth through ICT investments, this implies that investing in IT goods is more beneficial than investing in IT services.

5.3 Firm size heterogeneity

Most of the literature has focused on large firms, often using survey data, but it is unclear whether these earlier findings can be generalized to the population of small firms, which represent the bulk of the economy. Tambe and Hitt (2012) indicate this to be a major shortcoming of the literature. To the best of our knowledge, only Tambe and Hitt (2012), Hyatt and Nguyen (2010) and Bloom, Draca, Kretschmer and Sadun (2010) investigated whether returns on ICT are related to firm size. While Tambe and Hitt (2012) found that large firms benefit more from ICT, Hyatt and Nguyen (2010) found the opposite and Bloom et al. (2010) did not find differences in returns on ICT between small and large firms. The average number of employees in the study of Tambe and Hitt (2012) is more than 10,000 employees, while in Hyatt and Nguyen (2010) and Bloom et al. (2010) this is respectively 237 and 400 employees. Figure A-2 of appendix A shows that our data set covers the firm size distribution more exhaustively. Mean and median employment in our data set is 10.4 and 2 employees, but our sample also contains very large firms with more than 10,000 employees. This allows to more adequately test whether a size premium exists in returns on ICT. We divide the population of firms into seven bins according to firm size and re-estimate the production function to retrieve a size bin specific output elasticity and marginal product of ICT in table 8.[17]

TABLE 8: RESULTS PER SIZE BIN

Firm size	# firms	β_l	β_{NICT}	β_{ICT}	ICT input share	Marginal Product ICT
≤ 5 employees	124,301	0.4333	0.2292	0.0952	0.0894	1.2991
6-10 employees	17,959	0.7659	0.1556	0.0705	0.0812	1.0436
10-25 employees	13,156	0.8085	0.1230	0.0877	0.0796	1.3078
26-50 employees	5,246	0.8500	0.1068	0.1051	0.0791	1.5702
50-100 employees	2,098	0.8167	0.0841	0.1152	0.0798	1.6943
100-250 employees	1,226	0.8437	0.1012	0.1725	0.0817	2.4453
> 250 employees	680	0.7403	0.1321	0.1959	0.0833	2.6783

Notes: The results in this table are from an ACF estimator. The production functions include industry and year fixed effects. Standard errors are clustered at the firm level and all output elasticities are significant at the 1% level, except in the size bin of >250 employees where the ICT capital coefficient is significant at the 18% level due to a small number of observations in this size category.

In section 5.1, we found an average ICT input share of 0.0853 and a marginal product of ICT capital equal to 1.35 for the entire private sector. Table 8 shows that there is heterogeneity in firm size underlying these results. While there is no clear correlation between firm size and the labor and non-ICT capital coefficients, there is a positive correlation between the output elasticity of ICT capital and firm size. Because the ICT

[17] In appendix E we move beyond split sample analyses and fully recognize firm heterogeneity by identifying firm specific output elasticities with a random coefficients production function. This approach also shows a positive relationship between firm size and the output elasticity of ICT capital.

input share is relatively constant across the firm size distribution, the marginal product of ICT capital increases with firm size. In line with the findings of Tambe and Hitt (2012), we find that large firms benefit more from ICT. This upward trend in the marginal product of ICT capital also appears at more disaggregated levels of the firm size distribution, see figure A-3 in appendix A.

It is possible that the ICT capital coefficient is picking up omitted complementary intangibles. For example, management practices are positively related to ICT intensity (Bloom et al., 2012; 2014). As large firms are typically better managed (Bloom and Van Reenen, 2007), differences in returns across the firm size distribution could partly represent unmeasured management quality. If this is not controlled for, the estimated return on ICT capital could be biased upwards. Although we use state of the art techniques to control for unobserved productivity in estimating the output elasticity of ICT capital, these only control for management insofar comprised in firm productivity. Under the assumption that management quality is fixed over time, a fixed effects model allows to validate the robustness of our results.[18] Table 9 shows the output elasticities of ICT capital for each firm size bin, with firms who have less than 5 employees as a reference category, with and without firm fixed effects.

TABLE 9: RESULTS FOR DIFFERENT SIZE BINS WITH FIXED EFFECTS

VA production function	(1)	(2)	(3)	(4)
ICT capital	0.1095*** (0.0009)	0.0940*** (0.0010)	0.0722*** (0.0010)	0.0691*** (0.0011)
ICT capital * ≤ 5 employees		/		/
ICT capital * 6-10 employees		-0.0061*** (0.0018)		-0.0075*** (0.0014)
ICT capital * 10-25 employees		0.0045*** (0.0021)		-0.0068*** (0.0018)
ICT capital * 26-50 employees		0.0109*** (0.0031)		-0.0075*** (0.0026)
ICT capital * 50-100 employees		0.0254*** (0.0048)		0.0046 (0.0042)
ICT capital * 100-250 employees		0.0495*** (0.0074)		0.0109* (0.0062)
ICT capital * > 250 employees		0.0747*** (0.0112)		0.0266*** (0.0096)
# observations	1,083,534	1,083,534	1,083,534	1,083,5345
# firms	164,666	164,666	164,666	164,666
Firm fixed effects	NO	NO	YES	YES

Notes: Standard errors are clustered at the firm level. *** is significant at 1% level. * is significant at 10% level. Model (1) and (3) are the standard OLS production function with and without firm fixed effects. Models (2) and (4) are the same as Bloom et al. (2010) use to infer whether there is a size premium in returns on ICT capital: $y_{it} = \beta_l l_{it} + \beta_{IT} k_{it}^{ICT} + \beta_{NIT} k_{it}^{NICT} + \beta^{sj} s_{it}^{j} + \beta_{IT}^{sj}\left(k_{it}^{ICT} * s_{it}^{j}\right) + Z_{it} + \epsilon_{it}$ with s_{it}^{j} size bin dummies and Z_{it} the vector of year and industry controls. We show only β_{ICT} and β_{ICT}^{sj}, which measure the effect of ICT capital for firms with less than 5 employees and the additional effect according to the firm's size.

[18] The firm fixed effects estimator identifies whether there is a difference between the size bins in how within firm variation in ICT capital is related to within firm variation in output. It controls for any time fixed unobserved heterogeneity, which one can argue management to be, but also for returns on the part of the ICT stock that is persistent over time. Therefore, the firm fixed effects estimator is likely to underestimate the return on ICT capital.

Without accounting for firm fixed effects, the return on ICT capital is significantly higher for each size bin compared to the size bin just below. After accounting for firm fixed effects, we only find a significantly higher output elasticity of ICT capital for firms with more than 100 employees. This result implies that increasing ICT capital increases output more in the subgroup of firms with more than 100 employees than in smaller firms. The result that firms with less than 100 employees only have a higher output elasticity without accounting for firm fixed effects suggests that our ICT capital coefficient could indeed reflect unmeasured complementary assets to a certain extent. Table 10 further investigates whether the firm size premium in the return on ICT can be attributed to management, decentralization or skilled labor.

TABLE 10: LARGE FIRMS BENEFIT MORE FROM ICT

VA production function	(1)	(2)	(3)	(4)	(5)
Labor	0.3922***	0.5411***	0.5392***	0.3924***	0.3457***
	(0.0051)	(0.1180)	(0.1191)	(0.0051)	(0.0084)
Non-ICT capital	0.1198***	0.1059***	0.1083***	0.1198***	0.1415***
	(0.0015)	(0.0340)	(0.0339)	(0.0015)	(0.0023)
ICT capital	0.0584***	-0.0039	-0.0033	0.0584***	0.0806***
	(0.0012)	(0.0478)	(0.0487)	(0.0012)	(0.0019)
ICT capital * size	0.0126***	0.0223**	0.0226***	0.0126***	0.0110***
	(0.0006)	(0.0094)	(0.0010)	(0.0006)	(0.0010)
General Management		0.0741			
		(0.0646)			
People management			0.0424		
			(0.0526)		
Decentralization				0.0946***	
				(0.0157)	
Skilled labor					0.0228***
					(0.0042)
# observations	1,083,534	1,699	1,699	1,083,534	602,482
# firms	164,666	163	163	164,666	137,548
Firm fixed effects	YES	NO	NO	YES	YES

Notes: Standard errors are clustered at the firm level. *** is significant at 1% level. ** is significant at 5% level. * is significant at 10% level. The World Management Survey is a cross section so firm fixed effects cannot be included in that estimation. The number of observations in the regression with skilled labor is lower as we only observe this information for a subset of firms since 2008.

Bloom, Sadun and Van Reenen (2012) find that U.S. firms have a higher output elasticity on ICT capital than European firms and that this difference in the return on ICT becomes statistically insignificant after controlling for people management. To test whether better people management in large firms explains the output elasticity premium of ICT capital in large firms, we exploit data on management practices that we collected following the format of the World Management Survey in 163 Belgian manufacturing firms.[19]

[19] The World Management Survey is a worldwide initiative to measure management that has been run in over 20,000 firms across 35 countries. The survey consists of 18 questions on talent management, target setting, operations management and lean manufacturing. The average score across the 18 questions is used to measure 'management'. People management practices relate to promotions, rewards, hiring and firing. For more information about the World Management Survey, we refer to Bloom and Van Reenen (2007).

Estimating a production function including the people management score does not change the finding that large firms benefit more from ICT. Neither does our findings change when adding the overall management score. The firm size premium on ICT does not appear to be reflecting differences in management practices.

Acemoglu, Aghion, Lelarge, Van Reenen and Zilibotti (2007) show that decentralized firms are more productive and that this effect is stronger in ICT intensive industries. To test whether decentralization plays a role in explaining the productivity returns of ICT capital, we estimate a production function that includes a dummy indicating whether a firm has inward or outward foreign direct investments (FDI).[20] The coefficient on the interaction between firm size and ICT capital is not affected by including the FDI dummy, indicating that large firms do not benefit more from ICT due to higher decentralization.

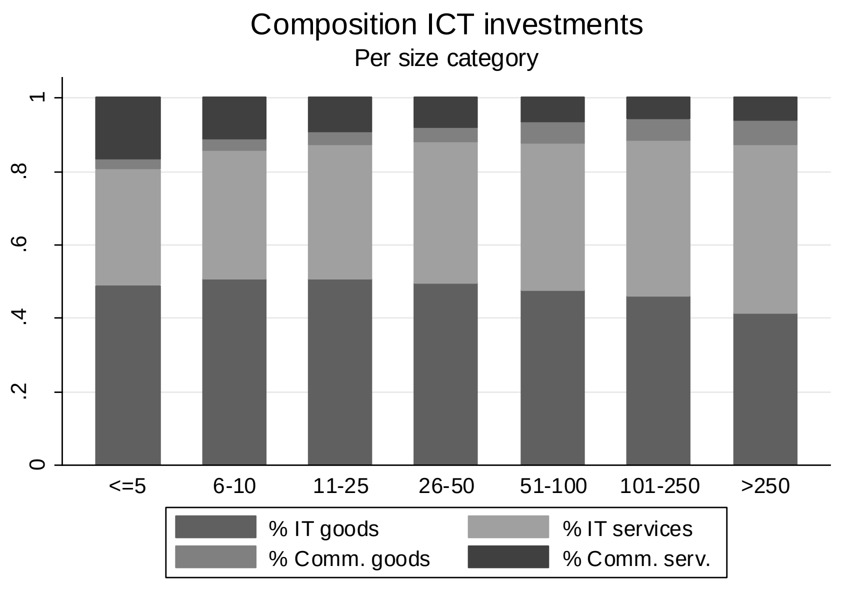
Bresnahan, Brynjolfsson and Hitt (2002) discuss the process through which ICT affects labor demand towards more skilled labor. Goos, Mannings and Salomons (2014) also show that there is a shift towards skilled jobs due to the surge in ICT investments. To investigate whether skilled labor is at the origins of the ICT output elasticity premium in large firms, we exploit information on the education level of employees. We add the share of highly educated employees to the model as a proxy for skilled labor and find that the interaction coefficient between employment and ICT capital remains unaffected. The same conclusion holds when we add wages, measured by the ratio of the wage bill to the number of employees, to proxy for labor quality as in Broersma, McGuckin and Timmer (2003). Differences in the degree of skilled labor are also not the reason why large firms benefit more from ICT.

Bloom, Garicano, Sadun and Van Reenen (2014) show that information technology and communication technology serve different uses. Communication technology investments result in a reduction of employee autonomy, because decisions can be passed to the center of the firm. Information technology investments have the opposite effect, facilitating employee decision making. We exploit our B2B data to infer how centralized decision making takes place in firms by investigating the differences in the investment shares of

[20] Acemoglu et al. (2007) measure decentralization as having foreign profit centers, which is closely related to our measure of decentralization. FDI participation is an indirect proxy for decentralization, and is also correlated to other unobservables. It is thus reassuring to see that the results hold after adding this control variable to the model.

ICT types across the firm size distribution. Figure 3 disentangles ICT investments, which are the basis of the ICT capital stocks, for the different size groups.

FIGURE 3: COMPOSITION ICT INVESTMENTS BY FIRM SIZE



Notes: Average industry shares after averaging the investment shares at the firm level.

The share of IT goods and communication services in ICT investments, and hence in ICT capital, decreases with firm size, while the share of IT services and communication goods increase with firm size. This pattern indicates opposing forces with regard to the level of decision making in the firm: IT goods investments push the level of decision making down, investments in communication goods are likely to push the level of decision making up. While there is no clear relationship between the level of decision making and the size premium in returns of ICT capital, figure 3 does show a clear decrease in the share of IT goods and an increase in IT services with firm size.

It is important to note that large firms are also more likely to provide IT and communication services in-house instead of buying them externally. Since in house ICT developments are not accounted for in our ICT investment data, we could possibly underestimate the ICT input share in large firms, leading to an upward bias in the marginal product estimate in large firms. There are two reasons why this phenomenon is unlikely to affect our results. First, figure 3 shows that the share of IT services increases instead of decreases with firm size. Second, this argument does not hold for the provision of ICT goods as these are unlikely to be produced in-house. When measuring excess returns using only ICT goods to construct the capital stock we get a similar picture as before, cf. figures A-4 and A-5 in appendix A.

5.4 Heterogeneity over time

We investigated the heterogeneity in returns on ICT in the cross section of our unique panel data set by looking at variation in the return on ICT across industries and across the firm size distribution. In the remainder of the paper, we exploit the time dimension of our data by looking at the evolution in the marginal product of ICT capital and by investigating how ICT capital contributes to aggregate output and productivity growth in section 5.5. Similar to earlier analyses, we show in table 11 a split sample estimation by year.

TABLE 11: RESULTS BY YEAR

Year	# firms	β_l	β_{NICT}	β_{ICT}	ICT input share	Marginal Product ICT
2003	77,277	0.6519	0.1962	0.1049	0.0667	1.5731
2004	80,055	0.6338	0.1958	0.1544	0.0716	2.1557
2005	86,205	0.6285	0.2107	0.1218	0.0771	1.5785
2006	90,977	0.6180	0.2147	0.1160	0.0797	1.4545
2007	94,577	0.6250	0.2013	0.1281	0.0818	1.5667
2008	95,029	0.6086	0.2239	0.1131	0.0862	1.3123
2009	96,160	0.6082	0.2187	0.1052	0.0917	1.1471
2010	96,963	0.6040	0.2286	0.1080	0.0939	1.1495
2011	99,547	0.6132	0.2172	0.1051	0.0961	1.0938
2012	97,425	0.6225	0.2131	0.0977	0.1016	0.9622
2013	95,116	0.6294	0.2122	0.0893	0.1060	0.8426

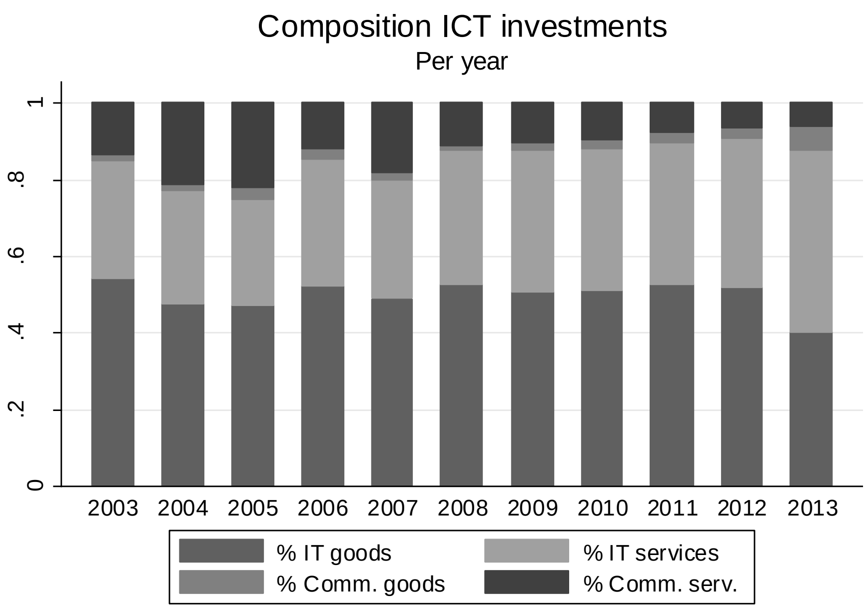
Notes: The results in this table are from the ACF estimator. Since the ACF estimator needs the first lag as instruments in the estimation, we lose the year 2002. The production functions includes industry fixed effects. Standard errors are clustered at the firm level and all output elasticities are significant at the 1% level.

There is no clear trend in the labor and non-ICT capital elasticities over time, but there is a clear downward trend in the output elasticity of ICT capital while the ICT input share increases over time. As a result, the marginal product of ICT capital decreases over time. While spending an additional euro on ICT had a gross return of 1.58 EUR in 2005, this almost halved by 2013 to 0.85 EUR.[21] A potential explanation for the downward trend is that it takes some time before ICT innovations spread out to other firms. Once they do, the premium of ICT investments drops over time.[22] In figure 4, we investigate the heterogeneity in returns on ICT over time further and exploit our B2B data to show the composition of ICT investments over time.

[21] We test in appendix D.5 whether our results on heterogeneity in returns on ICT across industries and firm size are related to the evolution over time in returns on ICT and find all earlier results to be robust.

[22] We thank an anonymous referee for this explanation.

FIGURE 4: COMPOSITION ICT INVESTMENTS BY YEAR



Notes: The average share of each ICT type in total ICT investments across firms by year.

Over time, the output elasticity of ICT capital declines simultaneously with an increase in the share of ICT investments attributed to IT services of about 15 percentage points and a decrease in the share attributed to communication services of 15 percentage points. The share of ICT investments attributed to IT goods and communication goods remain relatively stable around 50% and 3% of total ICT investments. The finding that the return on ICT decreases when the share of IT services increases is consistent with our findings in section 5.2. To validate whether the increase in importance of IT services can offer an explanation for the downward trend in the output elasticity of ICT capital, table A-7 in appendix A replicates the results of table 11 when constructing ICT capital with IT goods and communication goods only. If the change in the composition of ICT investments is the reason for the decline in the marginal product of ICT over time, one would expect the downward trend in the marginal product of ICT to disappear. However, we find this not to be the case and conclude that compositional changes are unlikely to be the reason behind the trend. Providing a full and detailed explanation of this trend would be interesting but lies outside the scope of the current paper and we leave this for future research.

5.5 ICT and (aggregate) productivity growth

Early work in the literature on returns on ICT capital was spurred by the famous quote of Robert Solow (1987) *"You can see the computer age everywhere but in the productivity statistics"*. This quote received a lot of attention because productivity growth indeed started to decline right at the moment computer investments took off. Houseman et al. (2015) showed that it is crucial to distinguish between ICT producing and ICT using industries. They found that productivity growth rates in the U.S. between 1997 and 2007 fall by almost half when computer producing industries are excluded. Also Acemoglu et al. (2014) found that ICT producing industries drive the positive impact of ICT investments on labor productivity. They conclude that the statement of ICT to improve productivity in all industries may be exaggerated.

To gauge the impact from ICT capital on aggregate GDP and aggregate productivity over the last decade, we use the Petrin and Levinsohn (2012, henceforth PL) decomposition and extend it by including ICT capital and non-ICT capital separately as production inputs. The intuition of the decomposition is shown in figure 1 and appendix B2 provides more details on the model. This decomposition allows us to shed light on the contribution of ICT capital deepening to aggregate value added growth, which learns whether firms did or did not invest (enough) in ICT capital. Furthermore, this decomposition contains a reallocation component for each production input. In a profit maximizing world, one would expect firms to reallocate resources towards its most profitable use. The reallocation components show the contribution to aggregate productivity growth from this mechanism. More specifically, it measures the contribution to productivity growth from reallocation of resources from low marginal value activities to high marginal value activities (relative to costs).[23] The ICT capital reallocation component learns whether firms who should (not) invest in ICT, namely those with (low) high returns on ICT capital, did (not) invest.

Tables 12 and 13 show the results of the PL decomposition in two steps. Table 12 decomposes economy wide value added growth in labor deepening, non-ICT capital deepening, ICT capital deepening and productivity growth. Table 13 further decomposes aggregate productivity growth into (i) within firm

[23] In a neoclassical setting without frictions, the value of the marginal product is equal to the marginal cost, leaving no room for improvements in aggregate productivity through reallocation of resources. In this scenario, the elasticity of output with respect to an input is equal to the share of expenditures for that input in total revenue. However, in a world of imperfect competition, markups, taxes and adjustment costs drive a wedge between marginal products, which leads to a possible role for reallocation of resources in increasing aggregate productivity growth (Basu and Fernald, 2002).

technical efficiency growth, which shows whether firms become more productive on average, (ii) productivity growth through reallocation of resources from low to high marginal value activities and (iii) a residual fixed cost component. Productivity growth from reallocation is further split in productivity growth from labor reallocation, non-ICT capital reallocation and ICT capital reallocation.

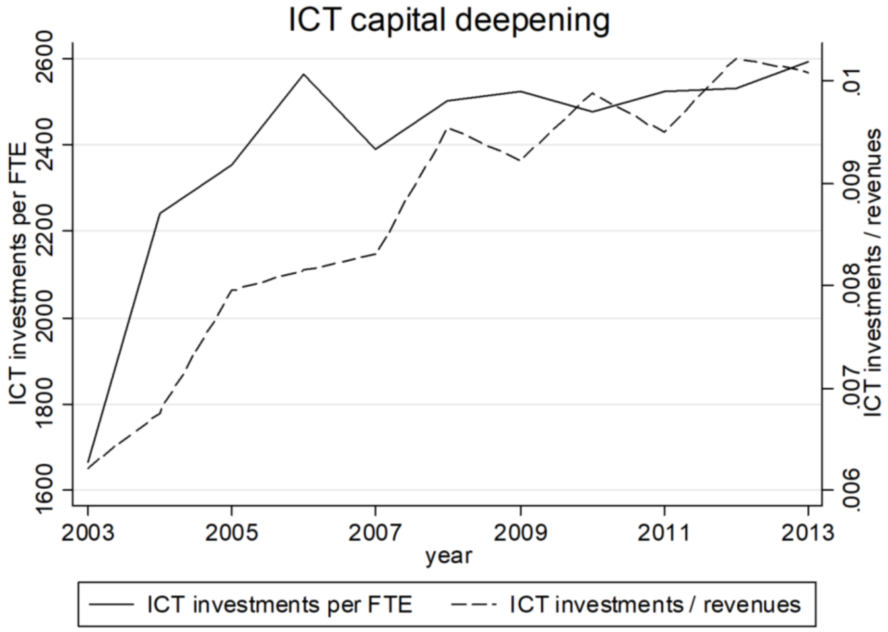
TABLE 12: PL DECOMPOSITION I

In percentages	Aggregate Output growth	Contribution from labor deepening	Contribution from non-ICT capital deepening	Contribution from ICT capital deepening	Contribution from productivity Growth
2003	3.45%	0.38%	0.95%	0.20%	1.91%
2004	4.62%	0.61%	0.46%	0.36%	3.19%
2005	1.04%	0.60%	0.19%	0.36%	-0.11%
2006	4.56%	1.05%	0.33%	0.54%	2.64%
2007	4.48%	1.48%	0.57%	0.21%	2.22%
2008	1.12%	0.71%	0.81%	0.17%	-0.57%
2009	-3.85%	-1.73%	-0.13%	0.13%	-2.12%
2010	3.30%	-0.12%	-0.29%	0.13%	3.58%
2011	3.29%	1.10%	0.25%	0.15%	1.79%
2012	0.46%	0.26%	-0.11%	0.14%	0.17%
2013	0.25%	-0.26%	-0.31%	0.11%	0.72%
Avg.	2.07%	0.37%	0.25%	0.23%	1.22%
St. Dev.	2.57%	0.87%	0.43%	0.13%	1.75%

Notes: The decomposition is based on a balanced subsample of 42,228 firms for which value added and the production inputs are positive and available for all years. Table A-12 in appendix A shows a comparison with other OECD countries.

On average, aggregate value added increased by 2.07% per year. It is apparent that this growth is largely driven by total factor productivity growth. The contribution of ICT capital deepening to aggregate value added growth is 0.23% on average. Especially during and after the great recession, there is a relatively low contribution to aggregate value added growth from ICT capital deepening. This finding suggests that firms reduced their ICT investment intensity over time. To obtain additional insights in the results on ICT capital deepening from the PL decomposition, figure 5 shows the evolution of the ratio of ICT investments per employee and the share of ICT investments in revenues.

Figure 5: ICT capital deepening



Notes: Employment weighted average of the ratio of real ICT investments to the number of full time equivalents and deflated revenues by year. The same sample is used as in the decomposition.

Average ICT investments per employee increased from about 1,700 EUR per employee in 2003 to 2,600 EUR per employee in 2006 and remained relatively constant afterwards. The same trend occurs when measuring ICT investment intensity as the ratio of ICT investments to revenues. The share of ICT investments in revenues almost doubled from 0.6% in 2003 to 1% in 2006 but stalled afterwards. This explains why the contribution of ICT capital deepening to output growth declines after the great recession.

The result that ICT investment growth is lower after the Great Recession indicates that firms became cautious in their investment decisions. The low investment intensity is believed to be one of the reasons for the productivity puzzle of the last decade. Section 5.4 shows a decrease over time in the marginal product of ICT, so it is possible that firms found it less opportune to invest in ICT after the Great Recession. Yet, the marginal product of ICT is still high in the most recent years of the sample, so one would expect firms to invest in ICT, especially large firms and firms in industries with excess returns on ICT.

To reconcile the heterogeneity in returns on ICT across industries and the firm size distribution with aggregate productivity and output growth, we look at the evolution of the reallocation component in table 13.

TABLE 13: PL DECOMPOSITION II

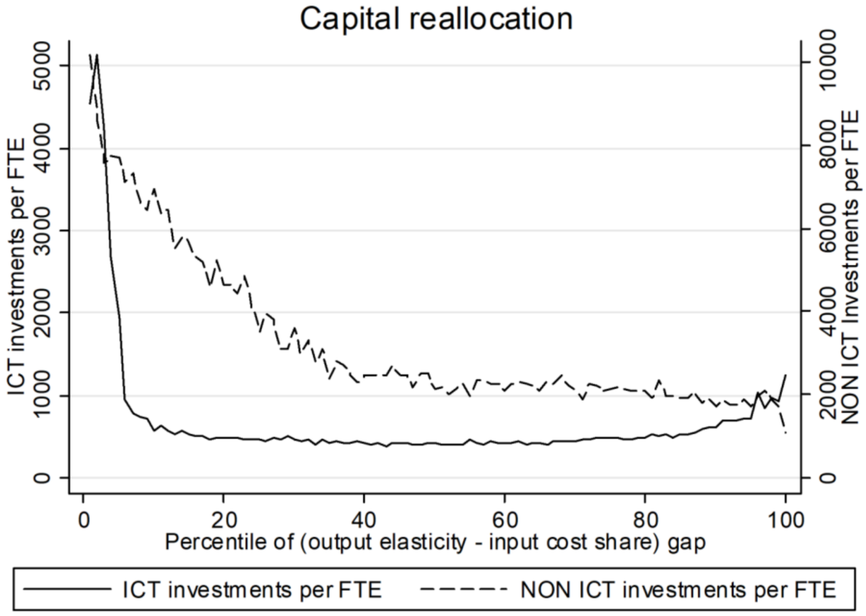
In percentages	Aggregate productivity growth	Within firm productivity growth	Productivity growth through reallocation: Labor	Productivity growth through reallocation: Non-ICT capital	Productivity growth through reallocation: ICT capital	Fixed cost
2003	1.91%	-3.03%	0.39%	0.72%	4.05%	-0.22%
2004	3.19%	0.02%	0.13%	0.88%	2.37%	-0.20%
2005	-0.11%	-2.78%	0.36%	0.61%	1.77%	-0.07%
2006	2.64%	0.98%	0.29%	0.31%	1.21%	-0.15%
2007	2.22%	0.94%	0.18%	0.31%	0.84%	-0.04%
2008	-0.57%	-1.81%	0.28%	0.08%	0.64%	0.25%
2009	-2.12%	-2.49%	0.22%	-0.24%	0.21%	0.18%
2010	3.58%	3.47%	0.08%	-0.16%	0.35%	-0.15%
2011	1.79%	0.98%	0.23%	0.02%	0.45%	0.11%
2012	0.17%	-0.75%	0.37%	-0.18%	0.32%	0.39%
2013	0.72%	0.19%	0.31%	-0.13%	0.18%	0.17%
Avg.	1.22%	-0.39%	0.26%	0.20%	1.13%	0.02%
St. Dev.	1.75%	2.00%	0.10%	0.39%	1.20%	0.21%

Notes: The decomposition is based on a balanced subsample of 42,228 firms for which value added and the production inputs are positive and available for all years.

Consistent with earlier research on the Belgian economy, we find that the largest share of productivity growth is driven by reallocation of resources (Van den bosch and Vanormelingen, 2017). We find that ICT capital reallocation, i.e. increases in ICT capital in firms that have high benefits compared to costs from increasing ICT capital, contributes on average 1.13% to aggregate productivity growth. As in our results on ICT capital deepening, we find that this average is entirely driven by the pre-recession period. After the great recession, the contribution of ICT capital reallocation, as well as non-ICT capital reallocation, dropped substantially. These result indicate that in the post-recession period there was only a modest impact from ICT capital reallocation to aggregate productivity growth, or in other words, our results suggest that firms with excess returns on ICT capital invested too little in ICT. The residual fixed cost term is relatively small in comparison to total reallocation, which indicates that reallocation of resources from low-value to high-value activities does a good job in explaining total reallocation.

Figure 6 shows the ICT investment intensity across the percentiles of the output elasticity – input cost share distribution. The graph indicates whether firms that have a large 'gap' between returns and costs from investing in (non) ICT capital, and hence are in the upper percentiles of the 'gap' distribution, accordingly invest in (non) ICT capital.

FIGURE 6: ICT CAPITAL DEEPENING AND CAPITAL REALLOCATION



Notes: The graph shows for each percentile of the distribution of the employment weighted gap between the output elasticity and the input cost share of (non) IT investments the value added weighted median next period (non) ICT investment intensity, expressed as the ratio of real (non) ICT investments per employee. The same sample is used as in the decomposition.

Figure 6 shows the ICT investment intensity in function of the opportunities associated with ICT investments. On the left are those firms for which the benefits from ICT investments are low, and on the right are the firms for which benefits from ICT investments are high. The figure shows a heavy left tail of observations for which the ICT investment intensity is relatively high while the investment opportunity 'gap' for ICT is low. The firms in this left tail are relatively small and ICT capital intensive with ICT capital being on average 30% of the total capital stock while this is only 10% in the other firms. Apart from the left tail, ICT investment intensity is relatively flat across the distribution. The same trend holds for non-ICT investments, where the left tail of the distribution is even heavier. This result is striking since one would expect that firms with large opportunities invest more. So there is a small group of firms that is ICT intensive and persistently invests in ICT while additional returns are rather low, while the majority of firms does not invest enough based on the difference between benefits and costs from ICT investments.

There could be external and/or internal frictions that make firms forego investments in new ICT, which could explain the observed suboptimal allocation of ICT investments. New ICT often disrupts current working practices so employees might be resistant towards adopting ICT, while actual usage is crucial for obtaining productivity effects (Devaraj and Kohli, 2003). Also, it is not obvious to align the adoption of new ICT systems with appropriate organizational commitment towards these new ICT systems (Steelman, Havakhor, Sabherwal and Sabherwal, 2019). These frictions might be especially relevant in large firms, compared to smaller firms where changing working routines is easier to implement. This could explain why the firms in the left tail of figure 6 are smaller in size than those on the right. Whatever the reason, the observed misallocation of ICT investments, together with our findings on low ICT capital deepening, can reconcile the paradox of identifying relatively high returns on ICT capital at the micro level, while they are not present or small at the aggregate macroeconomic level.

Tables A-8 – A-11 in appendix A present the results of the PL decomposition for the subset of manufacturing and services industries separately. In line with our expectations for the Belgian economy, which is characterized by a decline in manufacturing and shift to services, we find that labor deepening is the most important determinant for aggregate output growth in services while having a negative impact on output growth in manufacturing. On the other hand, productivity growth is by far the most important factor for value added growth in the manufacturing sector, while it is not that important in the services sector. The contribution from ICT capital deepening is relatively low, in services as well as manufacturing industries, and in both sectors the post-recession slowdown in the contribution of ICT and non-ICT capital deepening clearly stands out. So despite excess returns on ICT investments – especially in manufacturing industries as shown in section 5.2 – there was a slowdown in ICT investment after the Great Recession that coincided with a general slowdown in productivity growth. Taking a closer look at the determinants of aggregate productivity growth in manufacturing and services industries, we find that reallocation of resources explains about 60% of productivity growth in the manufacturing sector while it explains all of productivity growth in the services sector. Similar to the general downward trend over time in ICT capital deepening, we find a downward trend in the contribution of (non) ICT capital reallocation to aggregate productivity over time in both manufacturing and services industries.

Our findings of a low contribution from ICT capital deepening to aggregate output and a high concentration of ICT investments in a small group of firms is furthermore consistent with the empirical findings of declining business dynamism. Bijnens and Konings (2018) show that the decline in Belgian dynamism is highest for the most ICT intensive industries.

6. Conclusion

ICT has been transforming our society drastically over past couple of decades. However, due to lack of comprehensive firm level data on ICT investments, there has only been limited evidence on differences in the return on ICT across industries and across the firm size distribution. Moreover, there exists a disconnect in the ICT literature between microeconomic studies, which document substantial positive returns on ICT, and macroeconomic studies, which show a limited return of ICT on aggregate productivity growth, especially in Europe (Van Ark, 2014).

This paper uses a hitherto unexploited firm level panel data set on B2B ICT purchases from 2002-2013, which we combine with the income statements of firms to provide new evidence on the impact of ICT on productivity. The data set on B2B ICT purchases is administratively collected from tax declarations, hence all firm sizes and industries are represented in the data. The recorded ICT expenditures cover both tangible and intangible ICT purchases. This is a more comprehensive measure of ICT capital than in earlier studies, which often relied on the number of computers per worker and hence exclude the intangible component of ICT capital, e.g. Bloom et al. (2010). This paper contributes to the ICT literature by investigating who benefits most from ICT and by decomposing the relation between ICT and productivity at the firm and the aggregate level.

We find an output elasticity of ICT capital of 0.10, which implies that a 10% increase in ICT capital increases value added with 1.1%. This is higher than in earlier studies, where the output elasticity of ICT capital was estimated around 0.05-0.06 (Cardona et al., 2013). The gap between the output elasticity of ICT capital and its input share is substantial, and higher than for other production factors. Investing an additional euro in ICT increases value added on average with 1.35 EUR. The marginal product for ICT capital is higher than for other production inputs, a finding that is consistent with earlier studies.

The novelty in our study, apart from how we construct the ICT capital stock, is that we can uncover the heterogeneity in returns on ICT across industries, firm sizes and time and that we show how the composition of ICT investments relates to this heterogeneity. We show that both at the industry and firm level, there are differences in the output elasticity and marginal product of ICT capital. We find that the marginal product of ICT capital is higher in manufacturing industries than in services industries. Next, we show there exists a size premium in returns on ICT capital. This finding is robust to various estimation methods and other factors that might affect productivity growth such as labor quality, decentralization and management practices. Furthermore, we revisit the Solow paradox. Our results indicate that this paradox can be explained by two causes: (i) low ICT investments and (ii) misallocation of ICT investments. We find this effect to be particularly apparent after the Great Recession, which suggests that underinvestment in ICT is at least one of the reasons for the slowdown in productivity growth in the last decade.

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The manuscript guidelines of Information Systems Research commend a page limit of 38 pages. As suggested by the guidelines, the appendices below can be included in an online appendix.

Appendix A: Additional tables and figures

A 1. Tables

TABLE A- 1: LITERATURE OVERVIEW OF STUDIES IN WHICH ELASTICITY OF I(C)T CAPITAL IS ESTIMATED

Authors	Elasticity	Unit	Data		Region	# Obs. per year
			Start	End		
Our paper	+-0.11	Firm	2002	2013	Belgium	90.000
Van Reenen et al. (2010)	0.023	Firm	1998	2008	Europe	1900
Black and Lynch (2001)	0.05	Firm	1987	1993	U.S.	638
Black and Lynch (2004)	0.296	Firm	1993	1996	U.S.	284
Bresnahan et al. (2002)	0.035	Firm	1987	1994	U.S.	300
Brynjolfsson and Hitt (1995)	0.052	Firm	1988	1992	U.S.	n.a.
Brynjolfsson (1996)	0.044	Firm	1987	1991	U.S.	702
Brynjolfsson and Hitt (2003)	0.058	Firm	1987	1994	U.S.	1324
Dewan and Min (1997)	0.09	Firm	1988	1992	U.S.	773
Gilchrist et al. (2001)	0.021	Firm	1986	1993	U.S.	580
Brynjolfsson and Hitt (1996b)	0.048	Firm	1988	1992	U.S.	370
Lichtenberg (1995)	0.098	Firm	1988	1991	U.S.	1315
Tambe and Hitt (2012)	0.041	Firm	1987	2006	U.S.	1800
Bertschek and Kaiser (2004)	0.152	Firm	2000	2000	Europe	212
Bloom et al. (2010)	0.015	Firm	1995	2003	Europe	4809
Hempell et al. (2004)	0.041	Firm	1996	1998	Europe	972
Hempell (2005a)	0.06	Firm	1994	1999	Europe	1177
Mahr and Kretschmer (2010)	0.13	Firm	2000	2008	Europe	182
Hempell (2005b)	0.049	Firm	1994	1999	Europe	1222
Loveman (1994)	-0.06	Firm	1978	1984	Worldwide	60
Basant et al. (2006)	0.115	Firm	2003	2003	Asia	266
McGuckin and Stiroh (2002)	0.17	Industry	1980	1996	U.S.	10
Stiroh (2002a)	-0.071	Industry	1973	1999	U.S.	18
Acharya and Basu (2010)	0.031	Industry	1973	2004	Worldwide	384
O'Mahony and Vecchi (2005)	0.066	Industry	1976	2000	Worldwide	55
Venturini (2009)	0.138	Country	1980	2004	Europe	15
Dewan and Kraemer (2000)	-0.013	Country	1985	1993	Worldwide	36
Koutroumpis (2009)	0.012	Country	2002	2007	Worldwide	22
Madden and Savage (2000)	0.162	Country	1975	1990	Worldwide	43
Röller and Waverman (2001)	0.045	Country	1970	1990	Worldwide	21
Sridhar (2007)	0.15	Country	1990	2001	Worldwide	63

Source: Adapted from table 5 in Cardona et al. (2013).

TABLE A- 2: RAW CORRELATIONS

Raw correlations	Added value	Labor	Non-ICT capital	ICT capital
Added value	1			
Labor	0.86	1		
Non-ICT capital	0.61	0.50	1	
ICT capital	0.60	0.53	0.38	1

Notes: Raw correlations between dependent and independent variables. All variables are in logs.

TABLE A- 3: RESULTS MANUFACTURING (NACE 10-33)

VA Prod. Function	OLS	Firm Fixed Effects	First differences	ACF	CWDL
Labor	0.7176***	0.5892***	0.3923***	0.6514***	0.4987****
	(0.0040)	(0.0065)	(0.0076)	(0.0130)	(0.0170)
Non-ICT Capital	0.1873***	0.1081***	0.0769***	0.2231***	0.2728***
	(0.0034)	(0.0040)	(0.0044)	(0.0158)	(0.0696)
ICT Capital	0.1031***	0.0640***	0.0522***	0.1215***	0.2937***
	(0.0024)	(0.0026)	(0.0028)	(0.0072)	(0.0866)
# observations	141,898	141,898	122,032	121,754	113,619
# firms	16,416	16,416	16,416	16,416	16,416
Ind. & Year FE	YES	/	/	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level. The estimation sample is identical in number of firms. The number of observations is lower due to missing lags/instruments for some observations in one/multiple years for a firm in the First differences, ACF and CWDL estimators.

TABLE A- 4: RESULTS SERVICES (NACE 50-82)

VA Prod Function	OLS	Firm Fixed Effects	First differences	ACF	CWDL
Labor	0.6681***	0.4810***	0.3199***	0.6154**	0.4470****
	(0.0019)	(0.0026)	(0.0028)	(0.0047)	(0.0070)
Non-ICT Capital	0.1740***	0.1077***	0.0780***	0.1977***	0.4396***
	(0.0016)	(0.0018)	(0.0018)	(0.0071)	(0.0324)
ICT Capital	0.1103***	0.0728***	0.0632***	0.1202***	0.1460***
	(0.0012)	(0.0013)	(0.0014)	(0.0046)	(0.0344)
# observations	686,422	686,422	567,614	565,751	542,770
# firms	92,566	92,566	92,566	92,566	92,566
Ind. & Year FE	YES	/	/	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level. The estimation sample is identical in number of firms. The number of observations is lower due to missing lags/instruments for some observations in one/multiple years for a firm in the First differences, ACF and CWDL estimators.

TABLE A- 5: RESULTS PER INDUSTRY - EXCLUDING ICT SERVICES

Industry (NACE codes)	# firms	Labor	Non-ICT Capital	ICT Capital	ICT input share	Marginal Product ICT
Agriculture, Forestry and Fishing (1-3)	1,940	0.43	0.42	0.05	0.02	2.88
High Tech Manuf. (21; 26; 30)	2,474	0.73	0.18	0.14	0.05	2.76
Other Manuf. (10-33 except High Tech)	15,050	0.65	0.26	0.09	0.05	1.72
Utilities (35-39)	777	0.55	0.33	0.08	0.02	4.11
Construction (41-43)	27,567	0.64	0.26	0.08	0.02	3.15
Wholesale and Retail (45-47)	47,527	0.63	0.22	0.09	0.06	1.59
Transportation and Storage (49-53)	7,397	0.65	0.25	0.06	0.02	3.52
Accommodation and food serv. (53-56)	14,566	0.61	0.26	0.04	0.03	1.44
Information and Communication (58-63)	1,384	0.66	0.22	0.11	0.11	0.95
Financial and Insurance (64-66)	2,054	0.70	0.20	0.09	0.06	1.47
Real Estate (68)	3,275	0.50	0.37	0.09	0.08	1.10
Prof., Scientific & Tech. activities (69-75)	17,584	0.65	0.18	0.10	0.09	1.07
Admin. and Support activities (77-82)	7,928	0.65	0.25	0.09	0.07	1.26

Notes: Results obtained from the ACF estimator. All regressions include industry and year fixed effects. Standard errors are clustered at the firm level. All estimates are significant at the 1% level. The number of observations for mining and quarrying firms is low, therefore these are omitted from the table.

TABLE A- 6: RESULTS AT THE 2-DIGIT LEVEL

Industry	# firms	β_l	β_{NICT}	β_{ICT}	IT input share	Marginal Product ICT
10 Manuf. Food products	3433	0.62	0.31	0.10	0.04	2.60
11 Manuf. Beverages	163	0.72	0.27	0.08	0.04	1.98
13 Manuf. Textiles	844	0.57	0.28	0.12	0.07	1.75
14 Manuf. Wearing Apparel	435	0.63	0.23	0.14	0.08	1.86
15 Manuf. Leather	60	0.65	0.23	0.14	0.08	1.80
16 Manuf. Wood Products	756	0.64	0.27	0.09	0.05	1.86
17 Manuf. Paper Products	270	0.79	0.16	0.07	0.09	0.79
18 Manuf. Printing	1797	0.64	0.19	0.14	0.30	0.45
20 Manuf. Chemical Products	529	0.67	0.24	0.17	0.08	2.15
21 Manuf. Pharmaceutical Products	93	0.65	0.18	0.18	0.07	2.58
22 Manuf. Rubber and Plastic	667	0.70	0.20	0.10	0.06	1.86
23 Manuf. Other Mineral Products	1116	0.64	0.28	0.09	0.03	2.70
24 Manuf. Basic Metals	188	0.68	0.21	0.15	0.05	2.89
25 Manuf. Metal Products	3896	0.65	0.22	0.10	0.05	2.06
28 Manuf. Machinery and Equipment	1039	0.75	0.11	0.13	0.07	1.95
29 Manuf. Motor Vehicles	200	0.70	0.18	0.10	0.06	1.60
30 Manuf. Other Transport Equipment	88	0.87	0.08	0.10	0.09	1.14
31 Manuf. Furniture	990	0.69	0.23	0.09	0.05	1.70
32 Other Manuf.	755	0.62	0.24	0.14	0.07	1.93
33 Repair Machinery and Equipment	529	0.63	0.19	0.13	0.06	2.15
41 Construction of Buildings	6782	0.63	0.27	0.10	0.03	3.48
42 Civil Engineering	1078	0.63	0.29	0.08	0.03	3.03
43 Specialized Construction	22891	0.64	0.23	0.09	0.04	2.05
45 Wholesale, Retail Motor Vehicles	8262	0.64	0.20	0.14	0.10	1.39
46 Wholesale, excl. Motor Vehicles	19504	0.64	0.16	0.16	0.11	1.48
47 Retail, excluding Motor Vehicles	24148	0.54	0.22	0.12	0.10	1.31
49 Land Transport	5937	0.63	0.28	0.06	0.03	2.15
50 Water Transport	149	0.62	0.30	0.09	0.04	2.56
52 Support for Transportation	1692	0.65	0.16	0.12	0.08	1.60
53 Postal and Courier Activities	562	0.69	0.12	0.11	0.07	1.66
55 Accomodation	1602	0.50	0.30	0.14	0.07	2.17
56 Food and Beverage Services	16423	0.61	0.24	0.06	0.05	1.05
58 Publishing	527	0.76	0.11	0.15	0.21	0.71
59 Film and Music Publishing	748	0.56	0.20	0.20	0.21	0.94
64 Financial Services	1506	0.67	0.19	0.10	0.13	0.76
66 Auxiliary Financial and Insurance	701	0.70	0.16	0.16	0.16	0.99
68 Real Estate	3602	0.50	0.34	0.12	0.14	0.83
69 Legal and Accounting Services	4847	0.59	0.15	0.13	0.14	0.91
70 Act. of Head Offices & Consulting	5308	0.65	0.16	0.09	0.19	0.49
71 Architect, Engineering, Tech. Serv.	4376	0.64	0.15	0.15	0.15	0.99
72 Research and Development	152	0.72	0.16	0.19	0.10	1.95
73 Advertising and Market Research	2246	0.68	0.14	0.14	0.26	0.56
74 Other Prof., Scient. & Tech. Serv.	947	0.60	0.17	0.16	0.22	0.70
75 Veterinary	271	0.34	0.32	0.10	0.08	1.31
77 Renting and Leasing	1373	0.45	0.43	0.14	0.09	1.58
78 Employment Activities	569	0.77	0.08	0.12	0.16	0.74
79 Travel and Tour Operators	879	0.70	0.10	0.16	0.22	0.73
80 Security and Investigation	197	0.74	0.14	0.11	0.08	1.28
81 Services to Buildings	3504	0.66	0.25	0.08	0.04	2.29
82 Office Administrative Services	2061	0.62	0.17	0.12	0.30	0.39

Notes: For NACE 1-3, 5-9, 12, 19, 26-27, 35-39, 51, 60, 63 and 65 there are not enough observations to estimate a separate production function with the ACF estimator. For these industries, the aggregate output elasticities of table 6 are used.

TABLE A- 7: HETEROGENEITY OVER TIME IN RETURN ON IT GOODS AND COMMUNICATION GOODS CAPITAL

Year	# firms	β_l	β_{NICT}	β_{ICT}	ICT input share	Marginal Product ICT
2003	67,874	0.6809	0.2090	0.0796	0.0432	1.8427
2004	70,154	0.6534	0.2182	0.1127	0.0466	2.4203
2005	76,332	0.6437	0.2308	0.0879	0.0485	1.8145
2006	81,488	0.6407	0.2341	0.0840	0.0489	1.7195
2007	85,785	0.6357	0.2362	0.0867	0.0483	1.7942
2008	86,898	0.6269	0.2497	0.0792	0.0501	1.5816
2009	88,496	0.6186	0.2455	0.0755	0.0519	1.4541
2010	89,810	0.6078	0.2651	0.0780	0.0516	1.5113
2011	92,766	0.6243	0.2491	0.0738	0.0523	1.4111
2012	91,237	0.6249	0.2408	0.0704	0.0531	1.3270
2013	89,689	0.6348	0.2524	0.0577	0.0519	1.1118

Notes: The results in this table are from the ACF estimator. Since the ACF estimator needs the first lag as instruments in the estimation, we lose the year 2002. The production functions includes industry fixed effects. Standard errors are clustered at the firm level and all output elasticities are significant at the 1% level.

TABLE A- 8: PL DECOMPOSITION I - **MANUFACTURING INDUSTRIES**

In percentages	Aggregate output growth	Contribution from labor deepening	Contribution from Non-ICT capital deepening	Contribution from ICT capital deepening	Contribution from productivity growth
2003	2.89%	-0.67%	0.75%	0.11%	2.70%
2004	5.77%	-0.24%	0.47%	0.23%	5.32%
2005	-0.62%	-0.43%	0.35%	0.33%	-0.87%
2006	4.95%	0.40%	0.17%	0.29%	4.08%
2007	5.57%	0.58%	0.56%	0.08%	4.34%
2008	0.63%	0.38%	0.77%	0.04%	-0.56%
2009	-7.28%	-2.36%	-0.13%	-0.08%	-4.71%
2010	4.29%	-1.46%	-0.41%	-0.04%	6.19%
2011	4.37%	0.43%	0.07%	0.06%	3.81%
2012	2.31%	-0.10%	-0.03%	0.08%	2.36%
2013	1.96%	-0.44%	-0.20%	0.03%	2.56%
Avg.	2.26%	-0.35%	0.22%	0.10%	2.29%
St. Dev.	3.76%	0.89%	0.40%	0.13%	3.19%

Notes: The decomposition is based on a balanced subsample of 7,035 services firms for which value added and the production inputs are positive and available for all years.

TABLE A- 9: PL DECOMPOSITION II - **MANUFACTURING INDUSTRIES**

In percentages	Aggregate productivity growth	Within firm productivity growth	Productivity growth through reallocation			Fixed cost
			Labor	Non-ICT capital	ICT capital	
2003	2.70%	-1.49%	0.56%	0.76%	3.30%	-0.43%
2004	5.32%	2.47%	0.01%	0.96%	2.11%	-0.23%
2005	-0.87%	-3.41%	0.24%	0.35%	1.78%	0.18%
2006	4.08%	2.39%	0.55%	0.10%	1.19%	-0.14%
2007	4.34%	3.38%	0.33%	0.19%	0.48%	-0.04%
2008	-0.56%	-1.24%	0.21%	0.09%	0.39%	-0.00%
2009	-4.71%	-4.43%	0.01%	-0.33%	-0.22%	0.25%
2010	6.19%	6.52%	0.21%	-0.30%	-0.08%	-0.16%
2011	3.81%	2.91%	0.33%	0.17%	0.25%	0.14%
2012	2.36%	1.34%	0.57%	-0.31%	0.29%	0.46%
2013	2.56%	2.12%	0.33%	-0.11%	-0.06%	0.28%
Avg.	2.29%	0.96%	0.30%	0.14%	0.86%	0.03%
St. Dev.	3.19%	3.25%	0.20%	0.42%	1.11%	0.26%

Notes: The decomposition is based on a balanced subsample of 7,035 services firms for which value added and the production inputs are positive and available for all years.

TABLE A- 10: PL DECOMPOSITION I - ***SERVICES INDUSTRIES***

In percentages	Aggregate output growth	Contribution from labor deepening	Contribution from Non-ICT capital deepening	Contribution from ICT capital deepening	Contribution from productivity Growth
2003	4.38%	1.15%	1.68%	0.44%	1.10%
2004	3.21%	1.17%	0.80%	0.60%	0.64%
2005	2.05%	1.26%	0.21%	0.40%	0.18%
2006	4.19%	1.31%	0.56%	0.60%	1.71%
2007	4.94%	2.12%	0.63%	0.33%	1.86%
2008	1.53%	1.20%	0.86%	0.32%	-0.85%
2009	-2.93%	-1.41%	-0.28%	0.32%	-1.57%
2010	3.07%	0.50%	-0.54%	0.27%	2.85%
2011	2.22%	1.49%	0.13%	0.24%	0.36%
2012	-1.60%	0.41%	-0.16%	0.20%	-2.06%
2013	-1.18%	-0.52%	-0.35%	0.15%	-0.45%
Avg.	1.81%	0.79%	0.32%	0.35%	0.34%
St. Dev.	2.63%	1.00%	0.66%	0.15%	1.50%

Notes: The decomposition is based on a balanced subsample of 26,589 services firms for which value added and the production inputs are positive and available for all years.

TABLE A- 11: PL DECOMPOSITION II - ***SERVICES INDUSTRIES***

In percentages	Aggregate productivity growth	Within firm productivity growth	Productivity growth through reallocation			Fixed cost
			Labor	Non-ICT capital	ICT capital	
2003	1.10%	-4.09%	0.34%	0.10%	4.98%	-0.23%
2004	0.64%	-2.76%	0.32%	0.43%	2.68%	-0.04%
2005	0.18%	-2.50%	0.55%	0.59%	1.84%	-0.30%
2006	1.71%	0.11%	0.17%	0.24%	1.35%	-0.16%
2007	1.86%	0.53%	0.09%	0.13%	1.07%	0.04%
2008	-0.85%	-2.49%	0.33%	-0.08%	0.85%	0.54%
2009	-1.57%	-2.38%	0.45%	-0.21%	0.47%	0.11%
2010	2.85%	2.50%	-0.03%	-0.05%	0.63%	-0.19%
2011	0.36%	-0.36%	0.10%	-0.02%	0.56%	0.08%
2012	-2.06%	-2.99%	0.32%	-0.13%	0.35%	0.39%
2013	-0.45%	-0.93%	0.41%	-0.28%	0.33%	0.03%
Avg.	0.34%	-1.40%	0.28%	0.06%	1.37%	0.03%
St. Dev.	1.50%	1.94%	0.17%	0.27%	1.39%	0.26%

Notes: The decomposition is based on a balanced subsample of 26,589 services firms for which value added and the production inputs are positive and available for all years.

TABLE A- 12: OECD GROWTH ACCOUNTING 1995-2014

	GDP growth	Labor deepening	ICT capital deepening	Non-ICT capital deepening	Multifactor productivity growth
Italy	0.43	0.12	0.21	0.34	-0.24
Japan	0.78	-0.47	0.34	0.28	0.63
Portugal	1.08	-0.09	0.32	0.70	0.18
Denmark	1.23	0.29	0.39	0.42	0.13
Germany	1.26	0.02	0.25	0.22	0.78
France	1.54	0.22	0.28	0.39	0.65
Belgium	**1.75**	**0.57**	**0.37**	**0.43**	**0.37**
Austria	1.78	0.32	0.33	0.45	0.69
Netherlands	1.83	0.57	0.36	0.44	0.48
Switzerland	1.90	0.50	0.45	0.48	0.47
Spain	1.97	1.05	0.25	0.84	-0.14
United Kingdom	2.08	0.59	0.28	0.38	0.84
Finland	2.11	0.46	0.21	0.30	1.17
Sweden	2.30	0.44	0.50	0.43	0.94
United States	2.35	0.46	0.44	0.42	1.03
Canada	2.50	0.97	0.35	0.50	0.69
New Zealand	2.56	1.28	0.57	0.53	0.17
Australia	3.20	1.07	0.47	0.84	0.81
Korea	4.26	-0.03	0.29	1.21	2.79
Ireland	4.44	1.15	0.28	1.01	2.03

Notes: OECD Compendium of Productivity Indicators 2016.

Our results from the PL decomposition on average GDP growth is close to that reported by the OECD. The OECD finds that 33% (~0.57/1.75) of GDP growth is due to labor deepening, 21% (~0.37/1.75) due to ICT capital deepening, 25% (~0.43/1.75) due to non-ICT capital deepening and another 21% (~0.37/1.75) due to multifactor productivity growth. We find for the period 2002-2013 an average GDP growth of 2.07% per year. Labor deepening explains on average 18% (~0.37/2.07) of GDP growth while non-ICT capital and ICT capital explain respectively 12% (~0.25/2.07) and 11% (~0.23/2.07) of GDP growth. Consistent with the OECD, we find that labor deepening has a larger impact on GDP growth than capital deepening. While the OECD reports a relatively small impact of multifactor productivity growth on GDP, we find that productivity growth is on average responsible for the largest share of GDP growth with 59% (~1.22/2.07). Our findings are closer to those of Van Beveren and Vanormelingen (2014). Easterly and Ross (2001) also show that in advanced economies productivity growth explains about 50% of GDP growth. It is possible that our results deviate because the OECD averages also contain the years 1995-2003, which we have no information on. As our results also indicate that capital deepening decreased over time in the Belgian economy, this could explain the differences between our findings and those of the OECD.

A 2. Figures

FIGURE A- 1: SCATTER PLOT VALUE ADDED AND ICT CAPITAL

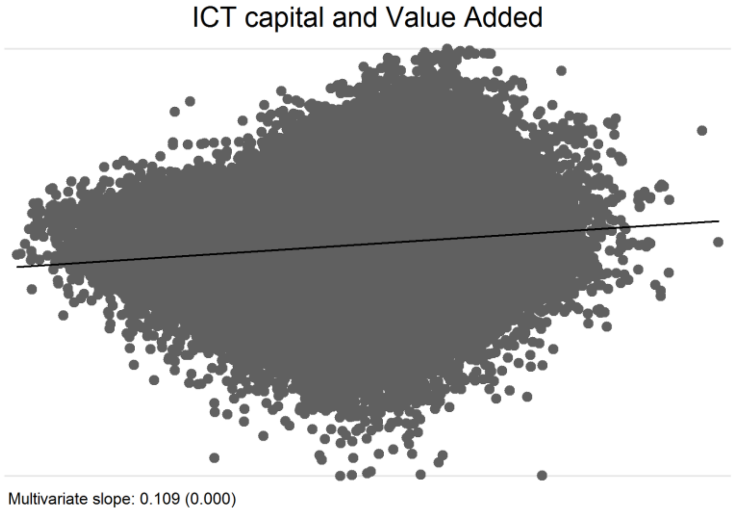
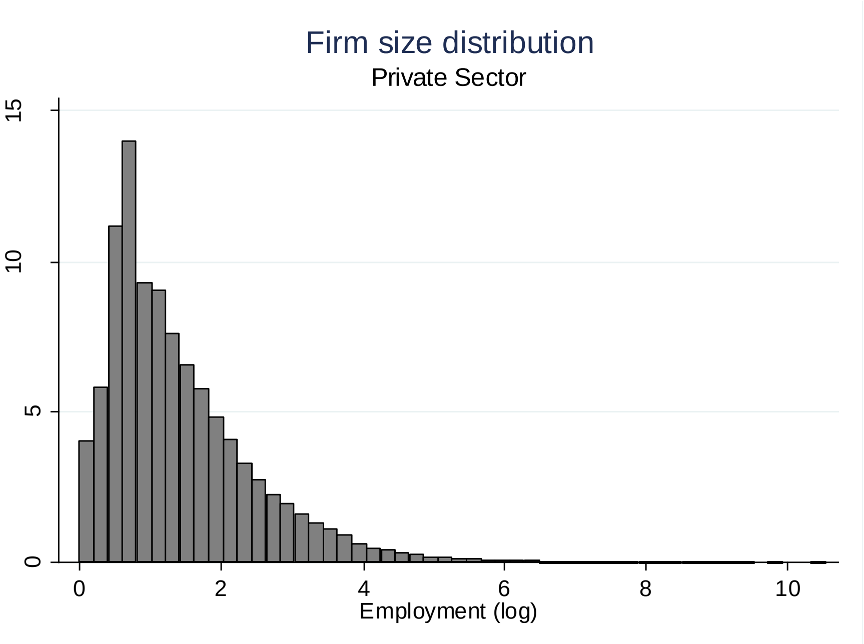


Figure A-1 shows the positive relationship between value added and ICT capital after removing variation in value added from non-ICT capital, labor and industry- and time-fixed effects for the entire private sector. The graph shows a positive association between ICT capital and added value, with a slope coefficient around 0.109. It is also apparent that there is a lot of heterogeneity underlying this effect. Disentangling this heterogeneity is the focus of this paper.

FIGURE A- 2: FIRM SIZE DISTRIBUTION OF THE SAMPLE



Notes: Histogram of average firm size, measured in full time equivalents, for all firms that are included in the estimations. Employment figures from the social balance sheets only include those who are in the personnel register of the firm.

FIGURE A- 3: MARGINAL PRODUCT OF ICT CAPITAL ACROSS FIRM SIZE DISTRIBUTION

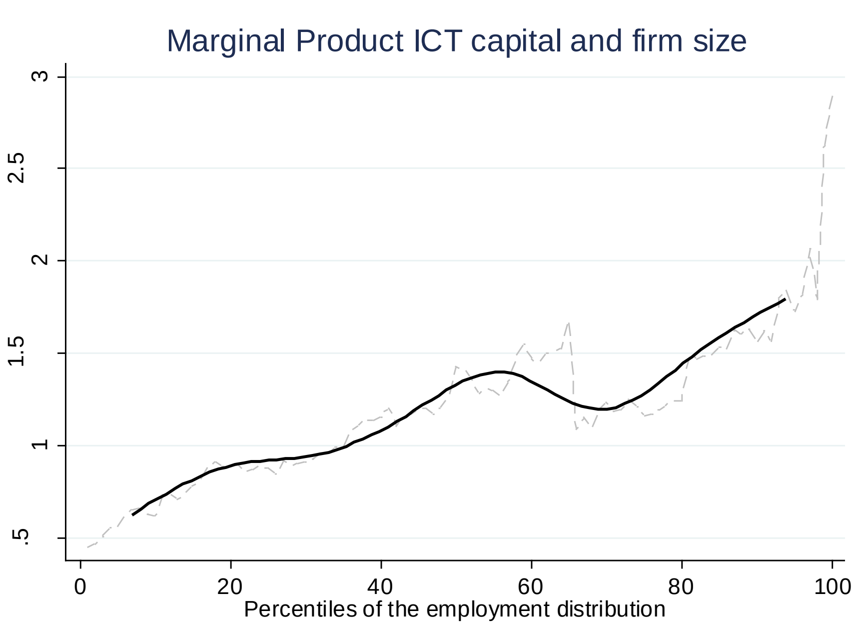


Table 8 shows that the marginal product of ICT capital increases with firm size based on a split sample analysis. However, these results might still obfuscate heterogeneity in the relationship between the marginal product of ICT capital and firm size within a size bin. Therefore, figure A-3 shows the relationship between the marginal product of ICT capital and firm size at a more disaggregate level. The graph shows the marginal product of ICT capital per percentile of the firm size distribution. Not surprisingly, the positive relationship between firm size and the return on ICT investments appears again.

FIGURE A- 4: RETURN ON ICT CAPITAL AND FIRM SIZE - ICT GOODS AND SERVICES

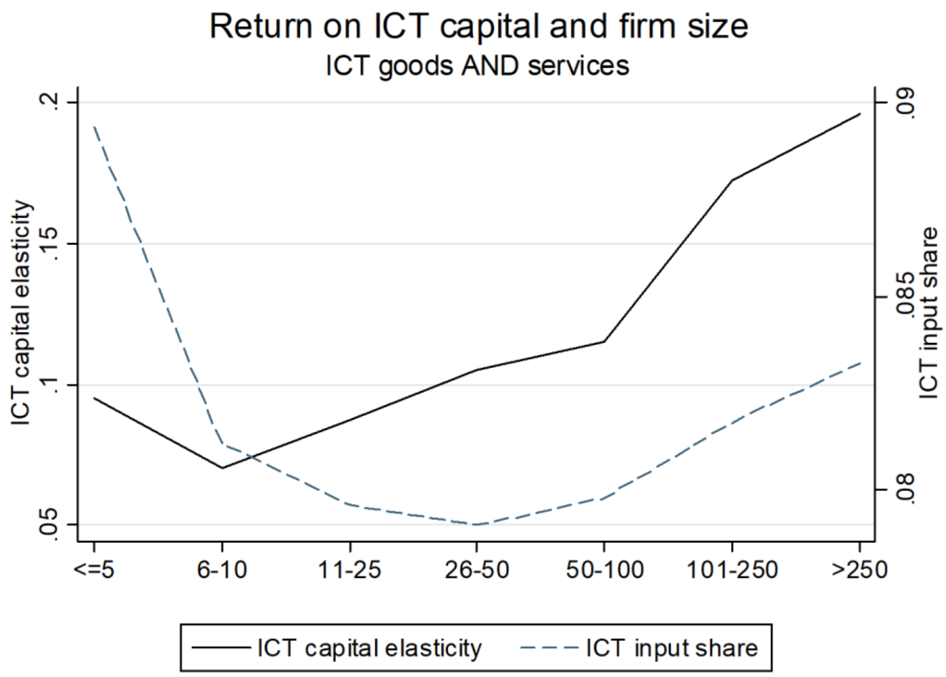


FIGURE A- 5: RETURN ON ICT CAPITAL AND FIRM SIZE - ICT GOODS

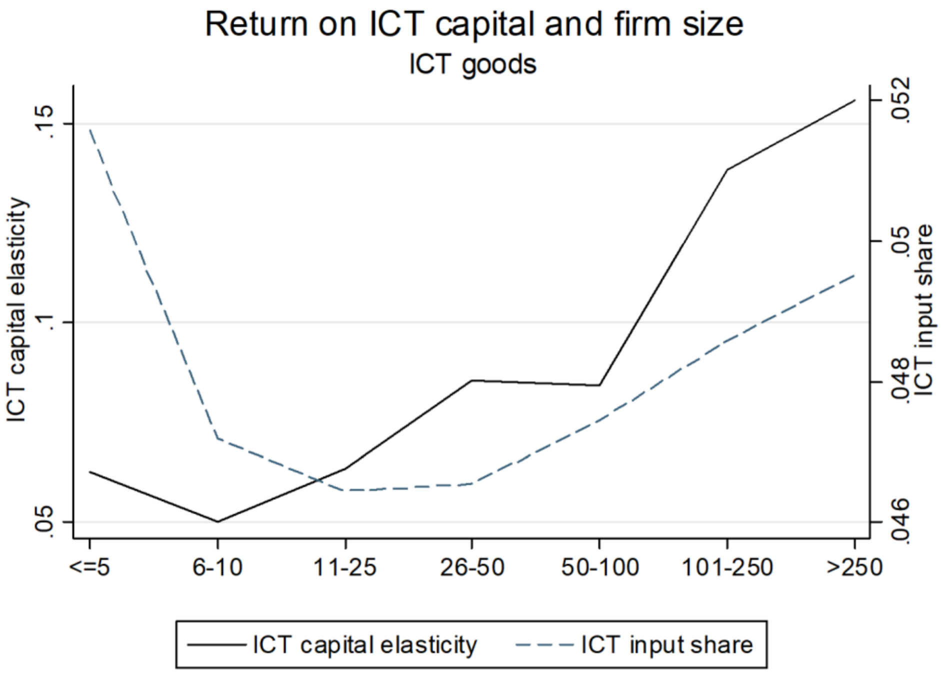
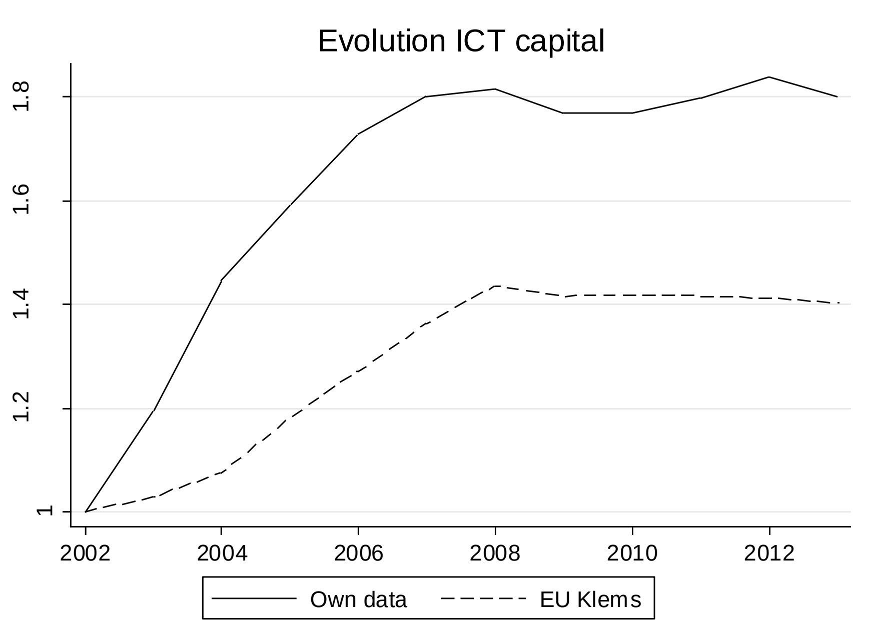


FIGURE A- 6: EVOLUTION ICT CAPITAL



Notes: This graph shows the evolution of total real ICT capital in our data set and the evolution of real ICT capital in EU Klems.

Appendix B: Estimation methods

B 1. Semiparametric production function estimation

This appendix provides more details on the GMM control function estimators that we use to overcome the simultaneity bias in production function estimation. Semiparametric estimation of production functions was introduced by Olley & Pakes (1996, henceforth OP). The idea is to control in the estimation of production functions for the unobserved productivity residual with other variables through which firms signal their productivity. The OP model relies on the firm's investment demand to control for the unobserved productivity. Levinsohn & Petrin (2003, henceforth LP) rely on the demand for material inputs instead of investment demand to proxy for unobserved productivity because investments are lumpy and often equal to zero. Ackerberg, Caves and Frazer (2015, henceforth ACF) extended the LP estimator to guarantee unbiased identification of the production function coefficients. Collard-Wexler and De Loecker (2016, henceforth CWDL) propose a similar estimation approach that relies on the firm's materials demand to proxy for unobserved productivity that is also robust to measurement error in capital. We detail the ACF estimator for our augmented production function, which is currently the workhorse model in the literature. We also introduce the novel estimator introduced by CWDL. We start from the augmented Cobb Douglas production function:

$$y_{it} = \beta_l l_{it} + \beta_{ICT} k_{it}^{ICT} + \beta_{NICT} k_{it}^{NICT} + \omega_{it} + \epsilon_{it} \tag{1}$$

The ACF estimation is based on the assumption that material expenditures are monotonically increasing in productivity, conditional on the other state variables. We can then substitute ω_{it} in equation (1) with the inverse of a non-parametric function of materials and the state variables, $\omega_{it} = f^{-1}(k_{it}^{IT}, k_{it}^{NIT}, l_{it}, m_{it})$. In a first step, we estimate the following equation:

$$\begin{aligned} y_{it} &= \beta_l l_{it} + \beta_{IT} k_{it}^{IT} + \beta_{NIT} k_{it}^{NIT} + f^{-1}\left(k_{it}^{IT}, k_{it}^{NIT}, l_{it}, m_{it}\right) + \epsilon_{it} \\ &= \tilde{\phi}_t(l_{it}, k_{it}^{IT}, k_{it}^{NIT}, m_{it}) + \epsilon_{it} \end{aligned} \tag{2}$$

In which m_{it} refers to material expenditures of firm i in year t. From this first step, we can only retrieve an estimate for value added, purified from ϵ_{it}, the true orthogonal residual that represents e.g. measurement error or machine breakdowns. In a second step we identify the input coefficients. Therefore, we introduce the second assumption that productivity evolves according to an exogenous first order Markov process (we relax this assumption in table A-15 of appendix D). Productivity is then a function of its lagged value and an unexpected shock:

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it} \tag{3}$$

The parameters of the production function are identified from using the following moment conditions on this unexpected shock in productivity:

$$E\left[(\xi_{it})\begin{pmatrix} l_{it} \\ k_{it}^{IT} \\ k_{it}^{NIT} \end{pmatrix}\right] = 0 \tag{4}$$

Practically, we can compute from each candidate vector of input coefficients an estimate for ω_{it} which we non-parametrically regress on ω_{it-1} to obtain an estimate for ξ_{it}. We then construct the sample analogue of (4) and estimate the input coefficients by minimizing this sample analogue.

The moment conditions are the result of assumptions on the timing of the input decisions. First, as is common in the literature, we assume that it takes one year to order and install capital goods. Consequently, investments entering the capital stock in period t were decided based on the information available in year $t-1$ and are by definition unrelated to the unexpected productivity shocks in t. Second, we make a similar assumption for labor, namely that it takes one period to hire new workers. This is a more strict assumption than is common in the literature, but can be justified by the large extent of hiring and firing costs in Belgium (see as well Konings and Vanormelingen, 2015) and can lead to more precise estimates (Ackerberg et al., 2015). We also estimated the production function while allowing ICT investments to be dependent on contemporaneous shocks in productivity as these are likely to be more flexible than non-ICT capital investments. To this end, we replace k_{it}^{ICT} by its lagged value in the moment conditions (see table A-14 in appendix D1).

In a recent paper, CWDL argue that capital stocks are particularly sensitive to measurement error. First, when constructing the capital stock using the PIM method, we assumed a common depreciation rate for all firms while this probably varies across firms and vintages of the capital stock. Second, since we do not observe the initial capital stock, we approximated it using a measure for the ICT capital intensity of the firm and the book value of all tangible fixed assets (see appendix C3). This procedure could introduce as well measurement error in the capital stock. CWDL propose a novel estimator that deals with this measurement error while controlling for unobserved productivity in the production function. To preserve the linear structure of the estimation equation, they suggest to write productivity as an AR(1) process. The counterpart of equation (2) with the CWDL extension is then:

$$y_{it} = \beta_l l_{it} + \beta_{IT} k_{it}^{IT} + \beta_{NIT} k_{it}^{NIT} + \theta_{IT} k_{it-1}^{IT} + \theta_{NIT} k_{it-1}^{NIT} + \theta_l l_{it-1} + \theta_m m_{it-1} + \xi_{it} + \epsilon_{it} \quad (5)$$

In which m_{it-1} refers to lagged material demand and the θ parameters combine the productivity persistence and production parameters. CWDL suggest to instrument the capital stock variables with lagged investments.[24] The idea is that the investment variables contain less measurement error than the stock variables. As explained in appendix C1, we have detailed information on ICT and non-ICT investment flows. The following moment conditions are used for identification:

$$E\left[(\xi_{it} + \epsilon_{it}) \begin{pmatrix} l_{it} \\ i_{it-1}^{IT} \\ i_{it-1}^{NIT} \\ i_{it-2}^{IT} \\ i_{it-2}^{NIT} \\ l_{it-1} \\ m_{it-1} \end{pmatrix}\right] = 0 \quad (6)$$

With i_{it}^{IT} and i_{it}^{NIT} the investments in ICT capital and non-ICT capital.[25] In our main specification, we model ICT capital as a stock variable. The premise is that ICT capital is part of the production isoquant, i.e. ICT capital can be substituted with other production inputs. While this is the standard approach in the literature, it could be argued that ICT investments induce a shift of the production function, i.e. enable to produce more output with the same set of inputs, for example because of new technology embedded in ICT. We enrich our model to allow for this data generating process as in Doraszelski and Jaumandreu (2013) and De Loecker (2013) in table A-15 of appendix D1.

[24] Galuščák and Lízal (2011) propose a similar approach to account for measurement error in capital. Instead of investments, they instrument the capital stock with depreciation, employment and intermediate inputs.
[25] Note that this procedure corrects for measurement error due to imprecisely observing the depreciation rate and the initial capital stock but not for possible measurement errors in the investment variables themselves.

B 2. Petrin and Levinsohn Decomposition

This appendix gives more details on the Petrin and Levinsohn (2012, PL henceforth) decomposition used in the paper. In contrast to other decomposition methods (cf. among many others Baily et al. 1992, Foster et al. 2001, and Melitz and Polanec, 2015) who define aggregate productivity as the share weighted sum of firm level productivity, PL start of from the definition of aggregate productivity growth that is also used in aggregate statistics, namely aggregate productivity growth is the difference between the change in aggregate final demand and the change in total expenditures on primary inputs:

$$APG \equiv \sum_i P_i dY_i - \sum_i \sum_{ki} W_{ik} dX_{ik} \tag{1}$$

Where Y_i and P_i are respectively output of firm i used for final demand and its price. Likewise, X_{ik} and W_{ik} represent the quantity and price of primary input k used by firm i. In our application, the primary inputs are labor, non-ICT capital and ICT capital. Rewriting equation (1) in growth rates and using the fact that aggregate final demand is equal to aggregate value added:

$$APG_G \equiv \sum_i s_i d \ln VA_i - \sum_i \sum_{ki} c_{ik} d \ln X_{ik} \tag{2}$$

with APG_G aggregate productivity growth rate, $s_i = VA_i / \sum_i VA_i$, the share of value added of firm i in aggregate value added and $c_{ik} = W_{ik} / \sum_i VA_i$ the share of cost of input k in aggregate value added. Similar to other papers that look at the micro-level origins of aggregate productivity growth, PL decompose aggregate productivity growth in a technical efficiency term (TE) and reallocation term (RE):

$$\begin{gathered} TE \equiv \sum_i P_i d\omega_i \\ RE \equiv \sum_i \sum_k \left(P_i \frac{\partial Q_i}{\partial X_{ik}} - W_{ik} \right) dX_{ik} + \sum_i \sum_j \left(P_i \frac{\partial Q_i}{\partial M_{ij}} - P_j \right) dM_{ij} \end{gathered} \tag{3}$$

With ω_i the total factor productivity of the firm, the technical efficiency term in equation (3) is the same as in other decompositions. Aggregate productivity increases when individual firms become more productive. The reallocation looks somewhat different. Aggregate productivity increases if a unit of input is reallocated from a low-value activity to a high value activity. For example, if a laborer moves from firm i to firm s and its wage is the same in both firms, the value of output increases by $P_s \frac{\partial Q_s}{\partial L_s} - P_i \frac{\partial Q_i}{\partial L_i}$ while aggregate input use remains constant, leading to an increase in aggregate productivity. Likewise, P_j and M_j represent the price and quantity of intermediate input j and aggregate productivity goes up if intermediates are reallocated from low to high value uses. The advantage of defining the reallocation term in this way, is that productivity improvements through reallocation are now directly linked to productivity growth defined at the aggregate level (Petrin and Levinsohn, 2012).

Taking discrete time growth rates using Tornquist-Divisia approximations renders the decomposition used in the text. First, the growth rate of aggregate value added can be written as $\sum_i \bar{s}_{it} \Delta lnVA_{it} = \sum_i \sum_k \bar{c}_{ikt} \Delta lnX_{ikt} + APG_{Gt}$ showing the contribution of deepening of inputs and aggregate productivity growth in value added growth. Here, a bar over variable denotes the average over two subsequent time periods. For example, $\bar{s}_{it}$ is the average value added share of firm i from year $t-1$ to year t. The growth rate of aggregate productivity can on its turn be written as $APG_{Gt} = TE + RE + F$ where:

$$TE \equiv \sum_i \bar{s}_{it} \Delta \ln\omega_{it}$$
$$RE \equiv \sum_i \bar{s}_{it} \sum_k (\beta_{ik} - \bar{\alpha}_{ikt}) \Delta \ln X_{ikt} + \sum_i \bar{s}_{it} \sum_j (\beta_{ij} - \bar{\alpha}_{ijt}) \Delta \ln M_{ijt} \tag{4}$$

and F is an unobserved fixed cost term. Here β_{ik} is the output elasticity of input k in the value added production function and $\bar{\alpha}_{ikt}$ is the cost share of primary input k in value added, averaged over the years $t-1$ to t. We estimate value added production functions at the NACE 2 digit level using the ACF estimator and obtain the output elasticities and compute firm-level productivity as $\omega_i = \ln VA_i - \beta_L \ln L_i - \beta_{NICT} \ln K_i^{NICT} - \beta_{ICT} \ln K_i^{ICT}$. See table A.6 for the two-digit output elasticities. Industries not included in this table have too few observations to estimate a separate production function, for these industries we use the more aggregate technology parameters reported in table 6. Because we estimate value added production functions, we do not know the output elasticities of the intermediate inputs and we abstract from their reallocation terms. Given our main interest is to estimate the contribution of ICT capital to aggregate productivity, we do not consider this as a serious shortcoming. The reader should however bear in mind that part of the within plant productivity growth could be in fact due to the reallocation of intermediate products, because we compute productivity using a value added production function (cf. Petrin et al., 2011). The advantage of this decomposition method is that aggregate productivity growth is defined in a way that is directly linked to aggregate growth in value added. Consequently, one can determine how economic growth depends on both deepening of inputs as well as on productivity growth, where the latter is than decomposed in its micro level origins. Since the PL decomposition is a mathematical identity and not an estimation, there are no confidence intervals available. This is standard in productivity decompositions, other examples are Baily et al. (1992), Foster et al. (2001) and Melitz and Polanec (2015).

Appendix C: Data

C 1. Sample construction

This appendix provides additional information on how the final data set is constructed. We start from the annual company accounts data of Belgian firms, to which we merge the other data sets based on the firm's unique VAT-number. Our panel covers the years 2002-2013 and initially counts 529,035 firms. We focus on the private sector and drop the ICT producing and ICT retail industries in table 1. For firms active in ICT producing industries, ICT purchases are mostly intermediate inputs instead of investments. For firms active in wholesale and retail of ICT goods and services, ICT goods are typically purchased for reselling. Therefore, we cannot use information on ICT purchases by these firms to measure ICT investment and ICT capital. This reduces the sample to 448,609 firms. Furthermore, we only retain firms for which we have information in their annual accounts on their industry code, value added, employment and capital, since these are needed for the estimation of production functions. This reduces the sample to 226,369 firms. To construct capital stocks, we need information from the VAT declarations and strictly positive investments in ICT and/or non-ICT capital in at least one year. For 11,159 firms we observe no VAT declarations, which is due to some activities being exempted from filing taxes.[26] From the remaining 215,210 firms, there are 25,855 firms that never invest in ICT and for which it is not possible to derive strictly positive capital stocks, which we require for theoretical consistency in a Cobb Douglas production function. In the estimation, we cannot use firms for which we do not observe all inputs in at least one year and since we estimate a log-linear Cobb Douglas production function, we also cannot include negative values. This reduces the sample with 11,412 firms. Finally, we exclude 13,277 firms for which material and/or labor expenditures are larger than total turnover. This results in a final sample of 164,666 firms that represent about 1.26 million employees, 108 billion in added value and 503 billion in turnover, which is a significant part of the Belgian private sector. This is the sample that we use in sections 5.1 – 5.4. The sample that is reported in the estimation results can be lower depending on the data requirements of the estimation method that is used. For example, the first differences and ACF estimator need at least one lag, while the CWDL estimator needs two lags.

[26] Article 44 of the VAT tax code describes in detail which activities are exempted. This are mainly activities in the socio-cultural sector, the financial and real estate sector.

C 2. Additional information VAT and B2B data

This appendix provides more information on the VAT data and B2B customer listings that we use to measure ICT investments and non-ICT investments. Each firm that is VAT liable has to periodically declare to the federal public service of finance the amount of investment goods it bought.[27] This is a direct measure for the total investments of a firm. The novelty in this paper comes from combining this information with information from the customer listings of firms, which VAT liable firms have to declare yearly to the federal public service of finance. In this listing, firms have to report the VAT number and associated revenues it obtained from each of its customers. Indirectly, this also learns how much each customers buys. We exploit this information to obtain ICT purchases for each customer. More specifically, we use the customer listings of firms that are active in NACE codes of ICT goods and ICT services industries as detailed in table 1. From their customer listings, we deduce how much ICT goods and ICT services each of its customers bought. For each customer, we sum its ICT purchases across all ICT producing firms. This is our firm level measure for Belgian ICT investments. We add to this the IT purchases from abroad, which we retrieve from the customs for imports coming outside the EU and the Intrastat trade survey for imports to Belgium coming from within the EU, to obtain the ICT investments of the firm. By deducting ICT investments from the total investments of the firm, we obtain the non-ICT investments of the firm.

Figure A-7 and A-8 show ICT intensity per 2 digit industry in the manufacturing and services sectors, approximated by the ratio of real ICT capital to total revenue. We aggregated the average firm level real ICT capital, real non-ICT capital and real sales up to the level of the 2-digit NACE sectors they belong to and took the ratio of the aggregate real ICT capital stock to aggregate real sales. The industries that are expected to have high ICT intensities show up where expected, which indicates that our measure of ICT investments adequately measures ICT in the firm.

[27] The customer listing serves taxation purposes, hence this listing only needs to contain entities that are also subject to the VAT system. This is the case for quasi all firms with limited liability, except some activities in the socio-cultural, financial and real estate sector that are exempted from taxes. See article 44 of the VAT tax code for more details on which activities are exempted. Natural persons are also excluded. Information on self-employed are not considered in this paper.

FIGURE A- 7: ICT INTENSITY IN MANUFACTURING INDUSTRIES

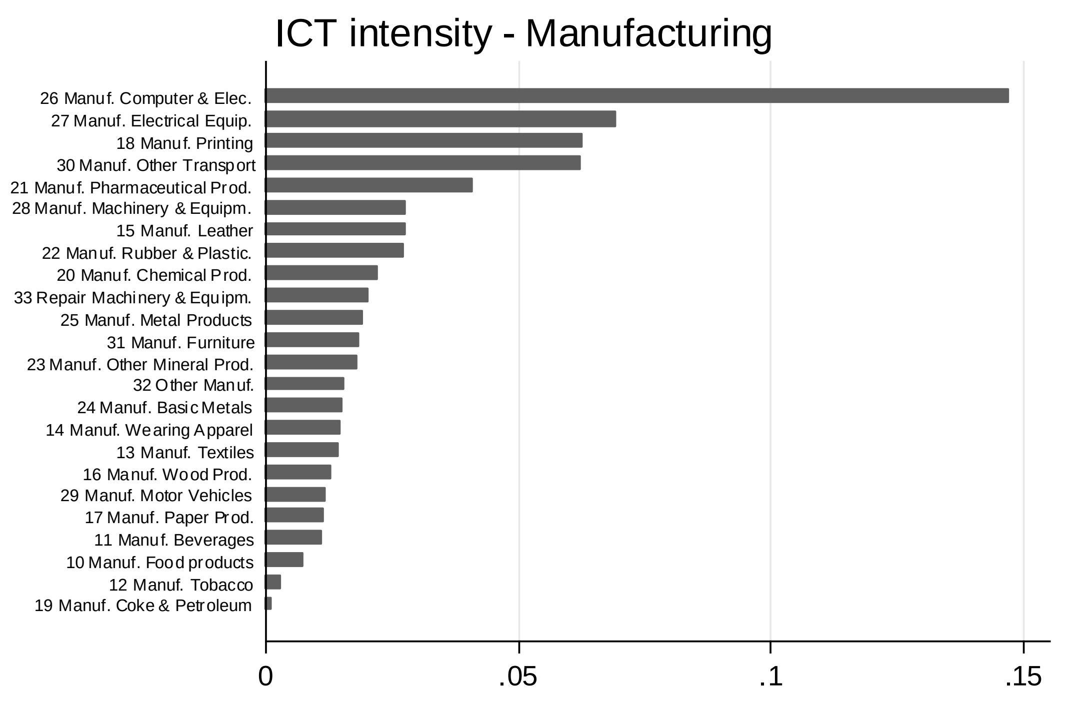
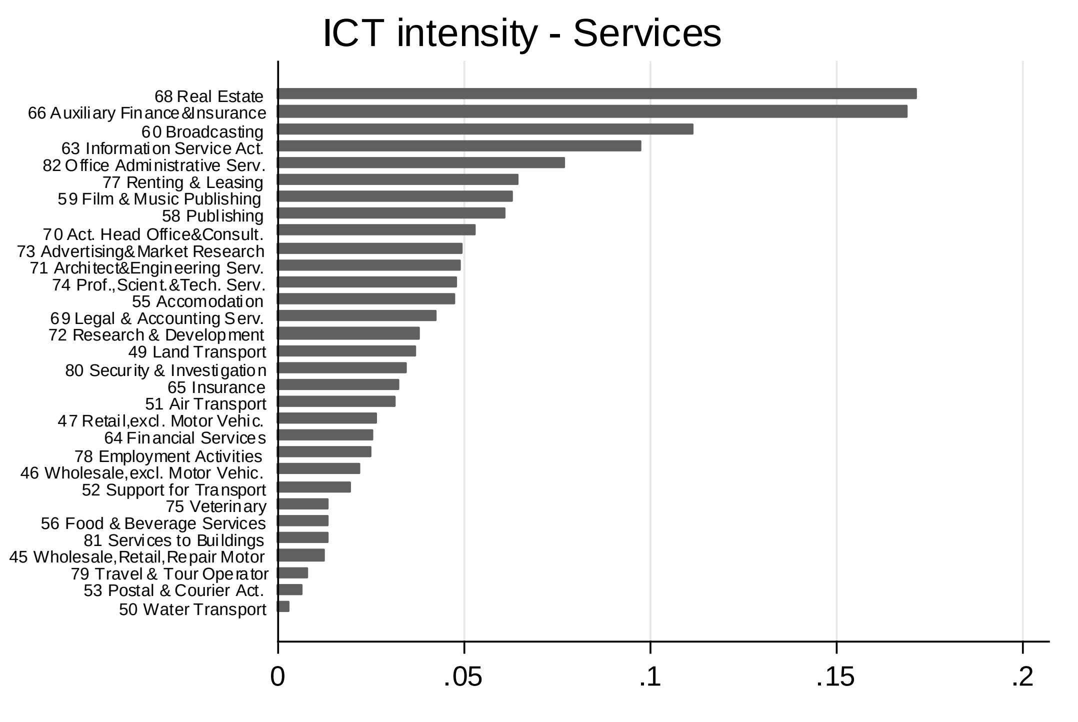


FIGURE A- 8: ICT INTENSITY IN SERVICES INDUSTRIES



C 3. Construction capital stocks

We construct real ICT capital and real non-ICT capital stocks using the Perpetual Inventory Method (PIM). This method allows us to optimally exploit our unique data on ICT purchases and total investments. The formula of the PIM is the following:

$$\widetilde{K}_{it}^{(N)ICT} = \widetilde{K}_{it-1}^{(N)ICT} * \left(1 - \delta^{(N)ICT}\right) + \tilde{I}_{it}^{(N)ICT} \tag{1}$$

In which $\widetilde{K}_{it}^{(N)ICT}$ refers to the real (non) ICT capital stock of firm i in year t, $\delta^{(N)ICT}$ refers to the depreciation rate for (non) ICT capital and $\tilde{I}_{it}^{(N)ICT}$ refers to real (non) ICT investments. We rely on data of the EU KLEMS initiative to turn the nominal values from our data set into real values.[28] The EU KLEMS data provide gross fixed capital formation deflators at the 2 two-digit level for the entire period of our sample. For non-ICT investments, we use the average of the gross fixed capital formation deflator from The Netherlands, France and Luxembourg. For ICT investments, we use the average of the 'computing equipment', 'computer software and databases' and deflators based on the average of these deflators from The Netherlands, France and Luxembourg. We take the average of these 'computing equipment' and 'computer software and databases' deflators as our ICT deflator. The EU KLEMS data also contain information on depreciation rates for both ICT and non-ICT capital. The yearly depreciation rate for ICT capital is fixed to 31.5 percent, consistent with ICT capital depreciation rates in other research. For non-ICT capital we assume a fixed depreciation rate of 15 percent.[29] The results are robust to deviations from these depreciation rates.

The first step in applying the PIM is calculating the initial ICT and non-ICT capital stocks. This is necessary because ICT capital is part of total tangible fixed assets but not reported separately in annual accounts.[30] The literature does not provide a straightforward solution to obtain initial capital stocks. In this appendix, we describe the approach used to obtain the results from the main body of the paper. In tables A16 - A20 of appendix D, we show that our results are robust to alternative ways of obtaining the (initial) capital stocks. To obtain the initial stocks, we predicted the firm's ICT capital intensity and use this to split initial

[28] More specifically, we rely on the capital input files from The Netherlands, France and Luxembourg of the September 2017 release. There is no capital input file for Belgium so we assume that the average of prices for ICT in The Netherlands, France and Luxembourg are close to those of Belgium.
[29] Production function estimates are similar using lower depreciation rates for non-ICT capital in the range of 8-10%.
[30] We refer to the European System of Accounts for further information.

nominal total tangible fixed assets into initial nominal non-ICT capital and initial nominal ICT capital. We use our unique data on ICT purchases and investments to predict this ICT capital intensity. First, we obtain nominal ICT and non-ICT investments from:

$$I_{it}^{ICT} = ICT\ purchases_{it} \text{ (see Table 1 for the purchases that are classified as ICT)}$$
$$I_{it}^{NICT} = Investments_{it} - I_{it}^{ICT} \tag{2}$$

We use the aforementioned gross fixed capital formation and ICT deflator to turn these nominal investments into real values. Next, we take the average of the real investment flows from the first 3 years the firm is in the sample. We do this because firms do not invest in ICT every year and to avoid errors in the initial capital stocks from outlier investments. We limit ourselves to the first 3 years because (i) longer periods could be less informative about the initial ICT capital stock (ii) firms can change their business model over time, i.e. becoming more or less ICT focused (iii) this is consistent with the finding that it takes some years before intangible stocks reach steady state in most industries (Knott et al., 2003).

We use the average real (non) ICT investment of the first 3 years to simulate the real (non) ICT capital stock under the assumption that this investment is representative for the stock. Following Hall and Mairesse (1995) and Hempell (2002) in earlier work on using the PIM to construct R&D and ICT capital stocks:

$$\widetilde{K}_{i1}^{(N)ICT} = \tilde{I}_{i0}^{(N)ICT} + \left(1 - \delta^{(N)ICT}\right)\tilde{I}_{i-1}^{(N)ICT} + \left(1 - \delta^{(N)ICT}\right)^2 \tilde{I}_{i-2}^{(N)ICT} + \cdots = \frac{\tilde{I}_{i1}^{(N)ICT}}{g_{it}^{(N)ICT} + \delta^{(N)ICT}} \tag{3}$$

With $\tilde{I}_{i1}^{(N)ICT}$ the real (non) ICT investment of the firm in the first year, $g_{it}^{(N)ICT}$ the 2-digit 5-year average growth rate of ICT capital before the firm enters the sample, which we obtained from EU KLEMS, and $\delta^{(N)ICT}$ the (non) ICT capital depreciation rate. Under the assumption that the average real (non) ICT investment of the first 3 years is representative for the investment strategy, we can then predict ICT capital intensity as follows:

$$ICT\ capital\ intensity_i = \widetilde{K}_{i1}^{ICT} / \left[\widetilde{K}_{i1}^{ICT} + \widetilde{K}_{i1}^{NICT}\right] = \frac{\tilde{I}_{i1}^{ICT}}{g_{it}^{ICT} + \delta^{ICT}} \Big/ \left[\frac{\tilde{I}_{i1}^{ICT}}{g_{it}^{ICT} + \delta^{ICT}} + \frac{\tilde{I}_{i1}^{NICT}}{g_{it}^{NICT} + \delta^{NICT}}\right] \tag{4}$$

This firm-level ICT capital intensity measure is by construction between 0 and 1. We use this ratio to split initial nominal total tangible fixed assets into initial nominal non-ICT capital and initial nominal ICT capital:

$$K_{i0}^{ICT} = ICT\ capital\ intensity_i * TFA_{i0}$$
$$K_{i0}^{NICT} = TFA_{i0} - K_{i0}^{ICT} \tag{5}$$

The aforementioned ICT deflator and gross fixed capital formation deflators are then used to turn these nominal initial stocks into real initial stocks. After obtaining the initial capital stocks from equation (5) and investments from equation (2) and deflating them with the deflators we constructed from EU KLEMS, equation (1) learns how to obtain real (non) ICT capital stocks at the firm level.

There are observations for which reported ICT purchases are larger than reported total investments. For such observations, we set non-ICT investments equal to zero. Given the novelty of our data, we investigated how this could potentially affect our analysis to guarantee that our estimates are not biased. Reporting higher ICT purchases than investments can occur for several reasons:

1) *Firms make mistakes in filling in the VAT declarations.* We checked the accounting regulations with accountants and auditors. They ensured that each purchase of ICT equipment should be registered as an investment. Nevertheless, they admit that firms sometimes make mistakes against this rule. Such mistakes could be seen as idiosyncratic errors and are not problematic for our analyses.
2) *Firms make mistakes on purpose in filling in the VAT declarations.* Although ICT equipment should be registered as an investment by law, reporting ICT purchases as intermediate inputs when profits are high could be interesting. This way, profits are lower and taxes are minimized. If this mechanism would be at play, ICT investments and hence the ICT capital stock would be underestimated for firms with high value added. This would result in an underestimation of the correlation between value added and ICT capital and hence a downward bias of the output elasticity of ICT capital. The output elasticity on ICT capital would then be a lower bound estimate of the true output elasticity.
3) *ICT purchases are ICT consumables, like cartridges and printing paper, rather than ICT equipment.* Such expenditures are reported as material costs instead of investments. The legal guideline on small ICT consumables that cost less than 1000euro, is to report these as material inputs. However, each purchase from an ICT producer larger than 250euro is included in our ICT purchases variable. Since not all ICT purchases are ICT investments, our ICT investments measure is probably overestimated. As a rough robustness check, we assumed 25% of ICT purchases to be ICT consumables rather than ICT equipment, this did not affect our estimates.
4) *ICT purchases are made in firms that are not active in the selected ICT goods and ICT services industries.* When firms purchase ICT equipment from suppliers that are not active in the NACE codes which we selected as

ICT equipment producers, e.g. if firms buy ICT equipment in supermarkets, this is not accounted for in our ICT investment measure. This would imply that our ICT investment measure is underestimated. The potential bias this would induce in our results works in the opposite direction as the potential concern raised about ICT purchases being consumables instead of investments. However, we believe that, in practice, the amount of ICT purchases that are either ICT consumables or made in firms that are not active in the selected NACE codes is rather small and therefore not problematic.

5) *ICT expenditures are effectively intermediate inputs instead of ICT investments.* Some industries can have a production process in which ICT purchases serve as inputs. This could for example explain why ICT purchases are higher than investments for 70% of observations in NACE 2680 (Manufacture of magnetic and optical media). Leaving out a set of industries, based on the ratio of observations for which ICT purchases exceed investments, does not alter our findings. We also tried to exploit the time dimension in our data to investigate whether ICT purchases end up in materials rather than in investments. More specifically, we estimated the following model:

$$\Delta m_{it} = \beta_0 + \beta_1 \Delta inv_{it}^{NICT} + \beta_2 \Delta sales_{it} + \beta_3 k_{it} + \beta_4 l_{it} + \beta_{5-510} \Delta purch_{it}^{ICT} * Ind_{4digit} + \varepsilon_{it}$$

This model allows to investigate for which four digit industries changes in ICT expenditures are correlated with changes in material expenditures. The model includes changes in gross output and changes in non-ICT investments to control for increases in material expenditures from increasing demand or non-ICT investments. Labor and capital are included to control for firm size. The purpose of this model is not to causally infer which industries have a production process in which ICT products are used as intermediate input. However, this simple model can help to check whether there is systematically more correlation between ICT expenditures and material expenditures in some industries. The results indicate that changes in material expenditures are mostly explained by changes in gross output. The coefficient of ICT purchases growth is neither higher nor more often significant for those industries in which there is a high percentage of observations that report higher ICT purchases than investments. These results support our assumption that ICT expenditures are not systematically reported as material input.

As final robustness check for the aforementioned potential issues, we did our analyses again after dropping all observations for which ICT purchases were larger than reported investments.

Table A- 13: Reduced sample (NACE 1-82)

Value Added Production Function	OLS		ACF	
	All observations	Reduced sample	All observations	Reduced sample
Labor	0.6739***	0.6337***	0.6226***	0.5872***
	(0.0015)	(0.0015)	(0.0038)	(0.0049)
Non-ICT Capital	0.1846***	0.2627***	0.2111***	0.3154***
	(0.0013)	(0.0015)	(0.0055)	(0.0101)
ICT Capital	0.1079***	0.0765***	0.1151***	0.0712***
	(0.0009)	(0.0010)	(0.0032)	(0.0011)
# obs	1,044,353	779,118	867,867	549,815
Industry & Year FE	YES	YES	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level.

Dropping observations for which ICT expenditures are larger than reported investments increases the non-ICT capital coefficient and lowers the ICT capital coefficient. This is hardly surprising since the highly ICT intensive firms are not included anymore and the production function reflects the importance of ICT capital in the production process.

Appendix D: Robustness checks

All empirical research comes with assumptions and choices on the most appropriate model. The results in the main body are based on timing assumptions that are standard in the literature. This section shows results for alternative data generating processes and different timing assumptions on the capital stocks.

D 1. Alternative Data Generating Processes

In the paper, the same data generating process as in Olley and Pakes (1996) is assumed: firms choose how much ICT investments they make in year *t* and these investments become part of the productive capital stock in year *t+1*. This way, there is no simultaneity between current productivity and ICT capital, i.e. ICT capital is chosen before current productivity was observed by the firm, and since current productivity is controlled for by the control function approach, the identification of the ICT capital coefficient is unbiased.

D 1.1 ICT investments become productive immediately

Identification problems arise when ICT investments become productive immediately. In the main body of the paper, we follow the standard assumption of the productivity literature that it takes one period to install capital. Investments I_t that are observed in the law of motion for capital, $K_t = K_{t-1} * (1 - \delta) + I_t$, are decided upon in $t - 1$ but only installed and paid in year t. Under the alternative data generating process that ICT investments become productive in the same year as they are ordered, I_t is decided upon, installed and paid in year t. This conveys an identification problem since the decision on I_t is now correlated with ξ_{it} in equation (3), i.e. the decision on how much ICT capital to employ in the production process in year t is correlated with the productivity shock the firm observes in year t. This discussion is similar to the arguments that Bond and Söderbom (2005) and ACF (2015) raise about the choice of labor. To solve for this potential simultaneity bias, the same way forward as with the labor variable can be applied, i.e. instrument ICT capital with its lagged value. Table A-14 shows the results from this modeling approach with the ACF estimator.

TABLE A- 14: ICT INVESTMENTS BECOME PRODUCTIVE IMMEDIATELY

Value Added Production Function	ACF (1)	ACF (2)
Labor	0.6226***	0.8013***
	(0.0038)	(0.0361)
Non-ICT Capital	0.2111***	0.1445***
	(0.0055)	(0.0103)
ICT Capital	0.1151***	0.1013***
	(0.0032)	(0.0261)
# observations	867,867	874,771
Industry & Year FE	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level.

Model (1) is the baseline model, in model (2) we instrument ICT capital with its lagged value. The results show that the ICT capital coefficient does increase significantly. Hence, the results in the paper serve as a lower bound for the scenario in which ICT investments become productive in the same period as they were purchased.

D 1.2 Learning from ICT investments

In the main body of the paper, we neglect the potential impact of ICT investments on the evolution of productivity. Equation (3) explicitly states $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$, so productivity is modeled as if it evolves according to an exogenous process. However, when firms invest in ICT in year t, this may affect the firm's expectations about productivity in year $t + 1$. Cassiman and Vanormelingen (2013), Doraszelski and Jaumandreu (2013) and De Loecker (2013) show the importance of controlling for learning from innovation, R&D and export when estimating production functions. We extend our model in a similar way as these authors to allow the firm's expectations on future performance (productivity) to be affected by current IT investments. We do this by modifying the second stage of the ACF estimation procedure such that the evolution of productivity explicitly includes ICT investments: $\omega_{it} = g(\omega_{it-1}) + \mathrm{Inv}_{t-1}^{\mathrm{ICT}} + \xi_{it}$. Table A-15 shows the results from modeling ICT investments in the law of motion in three different ways.

TABLE A- 15: LEARNING FROM ICT INVESTMENTS

Value Added Production Function	ACF (1)	ACF (2)	ACF (3)	ACF (4)
Labor	0.6226***	0.6225***	0.6224***	0.6182***
	(0.0038)	(0.0038)	(0.0038)	(0.0034)
Non-ICT Capital	0.2111***	0.2126***	0.2152***	0.2140***
	(0.0055)	(0.0058)	(0.0063)	(0.0059)
ICT Capital	0.1151***	0.1155***	0.1131***	0.0987***
	(0.0032)	(0.0037)	(0.0029)	(0.0049)
# observations	867,867	874,771	874,771	874,771
Industry & Year FE	YES	YES	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level. The number of observations for the ACF estimator is lower because it requires the first lag of the inputs.

Model (1) is the baseline model without allowing for learning from ICT investments. Model (2) includes a dummy in the law of motion that indicates whether or not a firm invested in ICT in year $t - 1$. Model (3) includes ICT investment intensity of year $t - 1$ in the law of motion and model (4) includes lagged ICT investments directly in the law of motion. Under learning from past ICT investments, we expect the ICT capital coefficient to be biased upwards since too much variation in output (controlling for the other production inputs) would be attributed to variation in ICT capital when the learning mechanism is not modeled. We find that the ICT capital coefficient hardly changes in specifications (2), (3) and (4) which allow for learning from past ICT investments experience.

D.2 Alternative ways to construct ICT capital

D 2.1 Only IT goods and IT services in ICT capital

In the data section we include all types of ICT in the ICT capital stock. Table A-16 shows the results when we only take IT goods and IT services, thus ignoring communications goods and services.

TABLE A- 16: RESULTS IT CAPITAL

Value Added Production Function	OLS		ACF	
	ICT	IT	ICT	IT
Labor	0.6739***	0.6726***	0.6226***	0.6254***
	(0.0015)	(0.0014)	(0.0038)	(0.0038)
Non-ICT Capital	0.1846***	0.1878***	0.2111***	0.2133***
	(0.0013)	(0.0013)	(0.0055)	(0.0062)
ICT Capital	0.1079***	0.1054***	0.1151***	0.1074***
	(0.0009)	(0.0009)	(0.0032)	(0.0029)
# observations	1,044,353	1,043,759	867,867	843,503
Industry & Year FE	YES	YES	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level. The number of observations for the ACF estimator is lower because it requires the first lag of the inputs.

The output elasticity of IT capital is very close to the output elasticity of ICT capital, this is not surprising since IT capital contributes the largest share to total ICT capital as shown in figure 1 of the paper.

D 2.2 Calculating initial capital stocks from more aggregated ICT intensity measures

Instead of using firm level ICT intensity measures, this robustness check shows the results when the initial ICT capital stock is derived from more aggregated ICT intensity measures. More specifically, we derive the initial capital stock from aggregate investment ratios at the two- and four-digit level instead of at the firm level.

TABLE A- 17: INITIAL CAPITAL STOCKS FROM AGGREGATED ICT INTENSITY

Value Added Production Function	OLS			ACF		
	(1)	(2)	(3)	(1)	(2)	(3)
Labor	0.6739***	0.6873***	0.6858***	0.6226***	0.6162***	0.6201***
	(0.0015)	(0.0014)	(0.0014)	(0.0038)	(0.0041)	(0.0039)
Non-ICT Capital	0.1846***	0.1807***	0.1791***	0.2111***	0.2320***	0.2277***
	(0.0013)	(0.0013)	(0.0013)	(0.0055)	(0.0063)	(0.0062)
ICT Capital	0.1079***	0.1022***	0.1043***	0.1151***	0.1083***	0.1076***
	(0.0009)	(0.0010)	(0.0009)	(0.0032)	(0.0028)	(0.0027)
# observations	1,044,353	1,163,271	1,163,169	867,867	944,457	944,374
Industry & Year FE	YES	YES	YES	YES	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level. Model (1) is the baseline model from the paper. Models (2) uses 2 digit ICT intensity and (3) uses 4 digit ICT intensity to obtain the initial ICT capital stock.

This robustness check shows that our results are robust to reducing cross sectional heterogeneity by calculating the initial capital stocks from more aggregate ICT intensity measures.

D 2.3 ICT capital calculated from ICT intensity instead of the PIM approach

The results in the main body of the paper and in other robustness checks applies the PIM method to obtain either ICT capital, non-ICT capital or both. The PIM approach is standard in the productivity literature. However, as discussed in appendix C3, there is some noise on the ICT investments variable. We argued in appendix C3 that there is no pattern in this noise. Yet, any noise in the investment variables could be exacerbated by the PIM approach. Therefore, the following robustness check does not make use of the PIM method. Instead, ICT capital is obtained by multiplying a firm's average ICT intensity with its total tangible fixed assets.[31] Non-ICT capital is obtained by subtracting ICT capital from total tangible fixed assets, as in Brynjolfsson and Hitt (1996) and Dedrick, Kraemer and Shih (2013).

TABLE A- 18: ICT CAPITAL CALCULATED FROM ICT INTENSITY

Value Added	OLS		ACF	
Production Function	(1)	(2)	(1)	(2)
Labor	0.6739***	0.7080***	0.6226***	0.6708***
	(0.0015)	(0.0014)	(0.0038)	(0.0023)
Non-ICT Capital	0.1846***	0.1461***	0.2111***	0.1213***
	(0.0013)	(0.0012)	(0.0055)	(0.0035)
ICT Capital	0.1079***	0.0638***	0.1151***	0.0555***
	(0.0009)	(0.0010)	(0.0032)	(0.0013)
# observations	1,044,353	939,822	867,867	750,303
Industry & Year FE	YES	YES	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level. Model (1) is the baseline model from the paper. Model (2) is the alternative specification of the robustness check.

Both the ICT and non-ICT capital coefficients are lower in model (2), which is unsurprising given that this approach ignores the time series variation in the capital stocks originating from investments. Therefore we interpret these coefficient estimates as an absolute lower bound.

[31] The average ICT intensity of a firm over the entire sample period is used since contemporaneous ICT intensity could still be subject to outliers in ICT investments.

D 2.4 Only ICT capital with PIM approach

In the paper, both ICT capital and non-ICT capital are obtained from using the PIM. In doing so, non-ICT investments are obtained by subtracting ICT purchases from total investments. As detailed in appendix C3, there could be mismeasurement in ICT purchases. If this would be the case, then this mismeasurement affects both the ICT and non-ICT capital stocks through errors in the investment flows. Therefore, this robustness check relies on data from the annual accounts for the non-ICT capital stock. The ICT capital stock is calculated with the PIM, and non-ICT capital as the residual of the book value of total tangible fixed assets, as in robustness check D.2.3.

TABLE A- 19: ICT CAPITAL WITH PIM & NON-ICT CAPITAL AS RESIDUAL OF TANGIBLE FIXED ASSETS BOOK VALUE

Value Added Production Function	OLS		ACF	
	(1)	(2)	(1)	(2)
Labor	0.6739***	0.6802***	0.6226***	0.6551***
	(0.0015)	(0.0013)	(0.0038)	(0.0032)
Non-ICT Capital	0.1846***	0.1668***	0.2111***	0.1267***
	(0.0013)	(0.0009)	(0.0055)	(0.0031)
ICT Capital	0.1079***	0.0941***	0.1151***	0.1111***
	(0.0009)	(0.0009)	(0.0032)	(0.0033)
# observations	1,044,353	1,037,128	867,867	809,110
Industry & Year FE	YES	YES	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level. Model (1) is the baseline model from the paper. Model (2) is the alternative specification of the robustness check.

The estimates, and hence qualitative findings derived in the paper, from the ICT capital coefficients are robust. The non-ICT capital coefficients are now lower, which can be explained by modeling it as a residual from tangible fixed assets, so not taking into account variation from non-ICT investments.

D 2.5 ICT capital stock on PIM and non-ICT capital stock based on book value

In all specifications, the non-ICT capital stock is basically a residual. This is so because non-ICT capital is (i) obtained from the PIM based on non-ICT investments that are calculated by subtracting ICT purchases from total investments or (ii) obtained from subtracting the ICT capital stock from the book value of tangible fixed assets. This implies that any mismeasurement in ICT investment or misspecification in the construction of the ICT capital stock shows up in the non-ICT capital stock as well. Therefore, this robustness check shows the results for calculating the ICT capital stock with the PIM method while using the reported book value of total tangible fixed assets as non-ICT capital stock.

TABLE A- 20: ICT CAPITAL WITH PIM & NON-ICT CAPITAL AS TOTAL TANGIBLE FIXED ASSETS BOOK VALUE

Value Added Production Function	OLS		ACF	
	(1)	(2)	(1)	(2)
Labor	0.6739***	0.6803***	0.6226***	0.6450***
	(0.0015)	(0.0014)	(0.0038)	(0.0032)
Non-ICT Capital	0.1846***	0.1766***	0.2111***	0.1108***
	(0.0013)	(0.0010)	(0.0055)	(0.0040)
ICT Capital	0.1079***	0.0865***	0.1151***	0.0974***
	(0.0009)	(0.0009)	(0.0032)	(0.0036)
# observations	1,044,353	1,072,618	867,867	864,489
Industry & Year FE	YES	YES	YES	YES

Notes: *** is significant at 1% level. ** is significant at 5% level. Standard errors are clustered at the firm level. Model (1) is the baseline model from the paper. Model (2) is the alternative specification of the robustness check.

Since the non-ICT capital stock now also contains ICT capital, both the coefficients for non-ICT capital and ICT capital should be lower. This is exactly what this robustness check shows.

D 2.6 Non depreciating ICT capital

An argument often made when estimating the returns on ICT capital is that ICT investments only contribute to output with a lagged effect. A survey on managers suggested it takes up to five years before ICT investments pay off (Brynjolfsson, 1993). Another study of Brynjolfsson, Malone, Gurbaxani and Kambil (1994) found that it took two to three years before organizational impacts of ICT are observed. In our main specification, we apply an annual geometric depreciation rate of 31.5%. Although it is common in the literature to do so, this approach may induce a discrepancy between capital productivity and capital wealth (Harper, 1982).[32] In this study, we are interested the productive ICT capital rather than the market value of ICT capital. Under lagged returns on ICT capital, the true current productive ICT capital stock is underestimated in the way we model it, which then would potentially result in a biased estimate of the IT output elasticity. For robustness, we show the estimates for non-depreciating ICT capital, which is the most extreme solution to cope with the argument that the productive ICT capital stock does not depreciate as fast as its market value.

TABLE A- 21: NON DEPRECIATING ICT CAPITAL

Value Added Production Function	OLS		ACF	
	(1)	(2)	(1)	(2)
Labor	0.6739*** (0.0015)	0.6861*** (0.0014)	0.6226*** (0.0038)	0.6010*** (0.0051)
Non-ICT Capital	0.1846*** (0.0013)	0.1613*** (0.0012)	0.2111*** (0.0055)	0.1850*** (0.0049)
ICT Capital	0.1079*** (0.0009)	0.1138*** (0.0009)	0.1151*** (0.0032)	0.1783*** (0.0064)
# observations	1,044,353	1,050,768	867,867	848,847
Industry & Year FE	YES	YES	YES	YES

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level. Model (1) is the baseline model from the paper. Model (2) is the alternative specification of the robustness check.

Since ICT capital is now assumed not to depreciate over time, the importance of ICT capital in the production process is now likely to be overestimated, which is what the results suggest. Whereas we interpret the results in robustness check D.2.3 as an absolute lower bound, we interpret these results as an absolute upper bound of the returns on ICT capital.

[32] The assumption of geometric depreciation avoids the distinction between productive capital and capital wealth. Productive capital reflects the efficiency of capital, which is in theory the marginal rate of technical substitution between old capital and new capital. Capital wealth reflects the market value of capital, which is obtained by depreciating the capital stock to account for changes in the real prices of the assets. Assuming that the efficiency of ICT capital declines geometrically over time by the ICT capital depreciation rate is not consistent with the finding of lagged returns on ICT capital.

D 3. Robustness on entry and exit

Tables A-22 – A24 show the results on industry heterogeneity, firm size heterogeneity and heterogeneity over time in the return on ICT capital for the fully balanced sample. This robustness check excludes firms that do not report for all years or have at least one missing observation over the full time span.

TABLE A- 22: INDUSTRY HETEROGENEITY – ROBUSTNESS ENTRY AND EXIT

Industry (NACE codes)	# firms	Labor	Non-ICT Capital	ICT Capital	ICT input share	Marginal Product ICT
Agriculture, Forestry and Fishing (1-3)	391	0.4510	0.3980	0.0641	0.0241	2.6545
High Tech Manuf. (21; 26; 30)	832	0.8020	0.1378	0.1300	0.0767	1.6966
Other Manuf. (10-33 except High Tech)	4,922	0.6776	0.2255	0.1119	0.0624	1.7938
Utilities (35-39)	196	0.5153	0.3663	0.0908	0.0323	2.8068
Construction (41-43)	6,311	0.7054	0.2120	0.0818	0.0295	2.7740
Wholesale and Retail (45-47)	10,656	0.6470	0.1722	0.1412	0.0747	1.8898
Transportation and Storage (49-53)	2,017	0.6643	0.2189	0.0666	0.0286	2.3244
Accommodation and food serv. (53-56)	2,553	0.6151	0.2451	0.0741	0.0337	2.2009
Information and Communication (58-63)	183	0.7465	0.1175	0.1490	0.1433	1.0397
Financial and Insurance (64-66)	217	0.8498	0.1215	0.0877	0.1244	0.7056
Real Estate (68)	283	0.6016	0.2666	0.1137	0.1204	0.9447
Prof., Scientific & Tech. activities (69-75)	2,397	0.7248	0.1375	0.1150	0.1438	0.7998
Admin. and Support activities (77-82)	1,384	0.6628	0.2512	0.1234	0.0962	1.2820

Notes: Results obtained from the ACF estimator. The production functions include industry and year fixed effects. Standard errors are clustered at the firm level. The mining and quarrying industry is omitted because of a low number of observations.

TABLE A- 23: FIRM SIZE HETEROGENEITY – ROBUSTNESS ENTRY AND EXIT

Firm size	# firms	β_l	β_{NICT}	β_{ICT}	ICT input share	Marginal Product ICT
≤ 5 employees	17,571	0.4585	0.2225	0.0857	0.0673	1.6008
6-10 employees	6,003	0.7529	0.1697	0.0762	0.0608	1.5559
10-25 employees	5,075	0.7830	0.1319	0.0907	0.0590	1.8778
26-50 employees	2,141	0.8068	0.1216	0.1085	0.0586	2.2493
50-100 employees	833	0.8287	0.0780	0.1100	0.0600	2.2200
100-250 employees	490	0.8108	0.1177	0.2081	0.0626	3.9691
> 250 employees	284	0.6641	0.1338	0.2110	0.0640	3.8538

Notes: The results in this table are from an ACF estimator. The production functions include industry and year fixed effects. Standard errors are clustered at the firm level.

TABLE A- 24: HETEROGENEITY OVER TIME – ROBUSTNESS ENTRY AND EXIT

Year	# firms	β_l	β_{NICT}	β_{ICT}	ICT input share	Marginal Product ICT
2003	32397	0.7212	0.1722	0.0855	0.0489	1.7499
2004	32397	0.6814	0.1744	0.1454	0.0527	2.7617
2005	32397	0.6705	0.1984	0.1153	0.0563	2.0496
2006	32397	0.6806	0.1819	0.1111	0.0570	1.9498
2007	32397	0.6707	0.1950	0.1162	0.0584	1.9894
2008	32397	0.6679	0.2040	0.0930	0.0630	1.4773
2009	32397	0.6513	0.2050	0.0893	0.0677	1.3189
2010	32397	0.6764	0.2068	0.1024	0.0702	1.4588
2011	32397	0.6504	0.2163	0.0994	0.0734	1.3534
2012	32397	0.6573	0.2084	0.0822	0.0793	1.0368
2013	32397	0.6632	0.2254	0.0795	0.0864	0.9195

Notes: The results in this table are from the ACF estimator. The production functions include industry fixed effects. Standard errors are clustered at the firm level.

D 4. Robustness to recession periods

Table A-25 shows the results for a split sample estimation in which we omitted the years 2008-2009 (Great Recession) and 2011-2012 (Euro-crisis).

TABLE A- 25: FIRM SIZE HETEROGENEITY – ROBUSTNESS RECESSION PERIODS

Firm size	# firms	β_l	β_{NICT}	β_{ICT}	ICT input share	Marginal Product ICT
≤ 5 employees	117,549	0.4470	0.2183	0.1001	0.0844	1.4488
6-10 employees	18,095	0.7658	0.1531	0.0805	0.0766	1.2682
10-25 employees	13,175	0.8073	0.1287	0.0978	0.0752	1.5497
26-50 employees	5,276	0.8288	0.1195	0.1286	0.0748	2.0413
50-100 employees	2,100	0.7643	0.1213	0.1369	0.0752	2.1423
100-250 employees	1,218	0.7714	0.1136	0.1807	0.0779	2.6954
> 250 employees	679	0.6803	0.1649	0.2378	0.0792	3.4239

Notes: The results in this table are from an ACF estimator. The production functions include industry and year fixed effects. Standard errors are clustered at the firm level.

D.5 Robustness to decline in ICT investments over time

The results show a slowdown in ICT capital deepening from 2008 onwards (figure 5). Tables A-26 and A-27 show that the findings on industry heterogeneity and firm size heterogeneity also go through for the period 2009-2013.

TABLE A-26: RESULTS PER INDUSTRY – RESTRICTED SAMPLE AFTER 2008

Industry (NACE codes)	# firms	Labor	Non-ICT Capital	ICT Capital	ICT input share	Marginal Product ICT
Agriculture, Forestry and Fishing (1-3)	1,571	0.44	0.42	0.05	0.03	1.87
High Tech Manuf. (21; 26; 30)	1,761	0.74	0.14	0.14	0.10	1.40
Other Manuf. (10-33 except High Tech)	11,315	0.63	0.27	0.09	0.08	1.14
Utilities (35-39)	568	0.58	0.30	0.07	0.05	1.66
Construction (41-43)	21,938	0.62	0.25	0.09	0.05	1.92
Wholesale and Retail (45-47)	35,174	0.60	0.20	0.12	0.12	1.05
Transportation and Storage (49-53)	5,657	0.65	0.22	0.06	0.04	1.42
Accommodation and food serv. (53-56)	11,811	0.62	0.26	0.05	0.06	0.86
Information and Communication (58-63)	749	0.61	0.14	0.19	0.27	0.70
Financial and Insurance (64-66)	1,260	0.72	0.14	0.08	0.17	0.49
Real Estate (68)	2,062	0.49	0.32	0.09	0.16	0.58
Prof., Scientific & Tech. activities (69-75)	11,199	0.63	0.15	0.11	0.19	0.57
Admin. and Support activities (77-82)	5,494	0.65	0.22	0.11	0.16	0.68

Notes: Results obtained from the ACF estimator. The production functions include industry and year fixed effects. Standard errors are clustered at the firm level. The number of observations for mining and quarrying firms is low, therefore these are omitted from the table.

The results for 2009-2013 show that all marginal products are lower than when using the full sample. This is consistent with the decline in the marginal product of ICT over time that is documented in the paper in section 5.4. More importantly, the finding on the ranking between the industries remains robust. It is still the case that manufacturing industries have a higher marginal product of ICT than services industries, with high tech industries having a larger marginal product of ICT than other manufacturing industries. Outside of manufacturing industries, we still find that utilities and construction have the highest marginal product and that services industries have a lower marginal product of ICT due to relatively high ICT input shares.

For the robustness check across firm size bins with the subset of data for 2009-2013, we merge the size bins at a more aggregate level for identification because we lose 1 out of the remaining 5 years of data as the ACF estimator needs lagged variables, and a large share of the variation across firms is accounted for by the industry and year fixed effects since the number of large firms within a two-digit code is relatively small.

TABLE A-27: RESULTS PER SIZE BIN – RESTRICTED SAMPLE AFTER 2008

Firm size	# firms	β_l	β_{NICT}	β_{ICT}	ICT input share	Marginal Product ICT
≤ 5 employees	92,510	0.4313	0.2433	0.0865	0.1021	1.0350
6-10 employees	16,488	0.7603	0.1480	0.0630	0.0935	0.8122
10-25 employees	12,270	0.8230	0.1029	0.0755	0.0913	0.9879
26-100 employees	6,689	0.8841	0.0702	0.0929	0.0915	1.2070
> 100 employees	1,769	0.7994	0.0624	0.1543	0.0936	1.9280

Notes: The results in this table are from an ACF estimator. The production functions include industry and year fixed effects. Standard errors are clustered at the firm level and all output elasticities are significant at the 5% level, except in the size bin of more than 100 employees the non-ICT capital coefficient is insignificant and the ICT capital coefficient is significant at the 19% level.

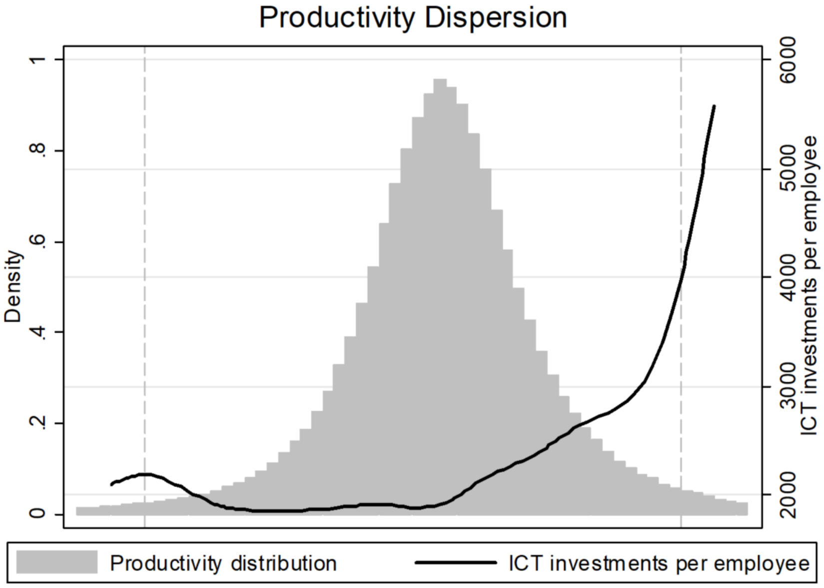
As in the results on split sample analysis across industries for the period 2009-2013, we find the marginal product of ICT to be lower than in the paper for all size bins, which is in line with the results in section 5.4. Consistent with the findings in the paper, the ICT capital output elasticity increases with firm size while the ICT input share remains constant across the firm size distribution, resulting in a positive correlation between firm size and the marginal product of ICT capital.

Appendix E: Extensions

E 1. ICT and TFP dispersion

Our results show that the productivity returns to ICT capital are positive and substantial for the average firm and we have shown that firm size matters for those returns. Another important question is whether ICT can explain TFP differences across firms. Syverson (2004) showed that, even within narrowly defined sectors, productivity dispersion is large, while Dunne, Foster, Haltiwanger and Troske (2004) found that computer investments are related to productivity dispersion across firms. We analyze to what extent this is also the case in our data. To get a sense on how much of the variation in productivity ICT explains, we investigate how much of the 90-10 TFP spread can be accounted for by ICT investments per worker. Figure A-9 shows how ICT investments evolve across the productivity distribution.

FIGURE A- 9: ICT AND TFP DISPERSION



We compare the explained spread in productivity from ICT investments with the spread in productivity explained by human capital. We focus on these two determinants because they are prominent drivers of productivity dispersion amongst firms, see Syverson (2011). As we compared returns on ICT capital in Belgium mostly with returns on ICT capital in the United States throughout the paper, we continue to do so in this part of our analysis. To this end, we apply the same analysis as Bloom, Brynjolffson, Foster, Jarmin, Patnaik, Saporta-Eksten and Van Reenen (2017) and show their results next to ours.[33]

[33] Importantly, to be able to compare our findings with Bloom et al. (2017) we follow their methodology and include only labor and capital (as reported in the annual accounts) as inputs when computing TFP.

TABLE A- 26: DRIVERS OF TFP DISPERSION

Dependent variable is demeaned TFP	Belgium			United States		
	(1)	(2)	(3)	(1)	(2)	(3)
IT investments per worker	0.0684*** (0.0010)		0.0655*** (0.0010)	0.015*** (0.003)		0.008*** (0.002)
Skills (share highly educated)		0.1566*** (0.0059)	0.0914*** (0.0060)		0.527*** (0.060)	0.126** (0.057)
Share of 90-10 explained	0.1813	0.0324	0.1925	0.0752	0.111	-
# firms	123,689	123,689	123,689	17,843	17,843	17,843

Notes: *** is significant at 1% level. Standard errors are clustered at the firm level. TFP is computed as in Bloom et al. (2017). The Belgian regressions are OLS regressions with as dependent NACE 4 industry demeaned TFP. IT investments per worker are equal to log(ICT purchases/FTE employment) and skills is equal to the ratio of highly educated employees to total employees. The US regressions are OLS regressions with as dependent NAICS 6 industry demeaned TFP. IT investments are investments in computers per employee and skills are measured by the share of employees with a college degree. The 'share of 90-10 explained' is obtained by multiplying the regression coefficient of the variable of interest with the 90-10 distribution spread of this variable and dividing this by the 90-10 spread of the dependent (TFP). Specification (3) of the United States cannot be directly compared to its counterpart of Belgium since the United States analysis also includes management and R&D as drivers of TFP, which we have no data on.

ICT investments per worker explain about 18% of the dispersion in productivity amongst firms in Belgium and only 8% in the U.S. Human capital explains about 3% in productivity dispersion amongst firms, while it explains around 11% of TFP dispersion in the U.S. Together, IT and human capital explain about 19 percent of productivity dispersion in the Belgian economy.

An important difference is that the average firm size in the study of Bloom et al. (2017) is 167 employees, while in our sample this is only 14 employees. When we drop firms with less than 50 employees from our sample, the coefficient on ICT investments per worker from model (3) decreases to 0.0489 ($t = 10.87, p < 0.01$) while the coefficient on the skills variable increases from 0.1566 to 0.4063 ($t = 14.25, p < 0.01$). The share of the 90-10 spread in TFP explained by ICT investments per employee remains similar at 0.1504 while the share of 90-10 spread in TFP explained by human capital increases from 0.0324 to 0.2233. Thus, human capital particularly explains TFP dispersion in large firms, while ICT investments per employee explain TFP dispersion in both small and large firms. Altogether, ICT investments per employee and human capital explain about 19 percent of TFP dispersion in the full sample and 27% of the 90-10 spread in TFP in the subsample of firms with more than 50 employees. Given that 50% of firm-level TFP is measurement error (Collard-Wexler, 2011; Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry, 2012), these findings suggest that IT and human capital actually explain up to 50% of total productivity dispersion in the Belgian economy.

E 2. Random Coefficients production function

We split our sample in bins to investigate the heterogeneity in the return on ICT capital for small and large firms. Although dividing the sample into bins of different firm sizes is intuitively appealing, from an econometric perspective this can be argued to be a rather arbitrary approach. Therefore, we augment our analyses with a random coefficients model in which we estimate firm specific output elasticities (Swamy, 1970). The random coefficient model fully recognizes firm heterogeneity and exploits the panel structure to obtain a firm specific output elasticity for the production inputs on top of an output elasticity that represents an average effect for the entire sample. Alcácer et al. (2013) illustrate the potential of random coefficient models in strategic management research and Kasahara, Schrimpf and Suzuki (2017) show how random coefficient production functions can prove to be usefulness in the industrial organization literature by allowing for production functions that are heterogeneous across firms beyond Hicks-neutral technology. We follow Knott (2008) in how to specify the random coefficient model:

$$y_{it} = (\beta_0 + \beta_{0,i}) + (\beta_l + \beta_{l,i})l_{it} + (\beta_{ICT} + \beta_{ICT,i})k_{it}^{ICT} + (\beta_{NICT} + \beta_{NICT,i})k_{it}^{NICT} + \epsilon_{it}$$

In which the coefficients with index i refer to the firm specific output elasticities and the coefficients without index i to the average output elasticity.[34]

TABLE A- 27: RANDOM COEFFICIENTS PRODUCTION FUNCTION (NACE 1-82)

Value Added Production Function	Fixed coefficient	Firm specific coefficient		
		P10	P90	Std. Dev.
Labor	0.5889*** (0.0019)	-0.1625	0.1504	0.1379
Non-ICT Capital	0.1024*** (0.0011)	0.0000	0.0000	0.0000
ICT Capital	0.0407*** (0.0008)	-0.0061	0.0053	0.0052
# obs.	388,764			
# firms	32,397			

Notes: *** is significant at 1% level. The estimation includes industry and year fixed effects. We limit the sample to a fully balanced panel to facilitate the identification and comparison of firm-specific parameters.

Although the focus of this paper is on ICT capital, it is worth noting that there is large firm level heterogeneity on the labor coefficient. In figures A-10 and A-11 we show the relationship between the ICT capital output elasticities and firm size. Figure A-10 shows that the average firm level ICT capital elasticity increases with firm size. The box plot in figure A-11 shows that the median firm level ICT elasticity increases while its variance decreases when moving along the firm size distribution.

[34] As in OLS, there are potential endogeneity issues in this specification. Kasahara et al. (2017) propose a possible way forward by extending the Gandhi, Navarro, Rivers (2013) framework. This is beyond the scope of this paper.

FIGURE A- 10: AVERAGE FIRM SPECIFIC ICT CAPITAL PER FIRM SIZE BIN

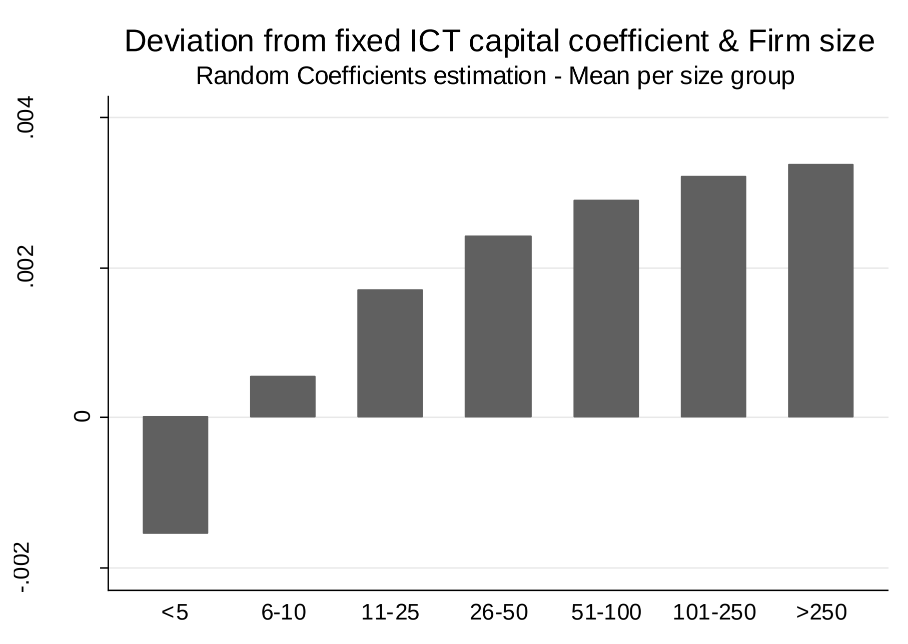
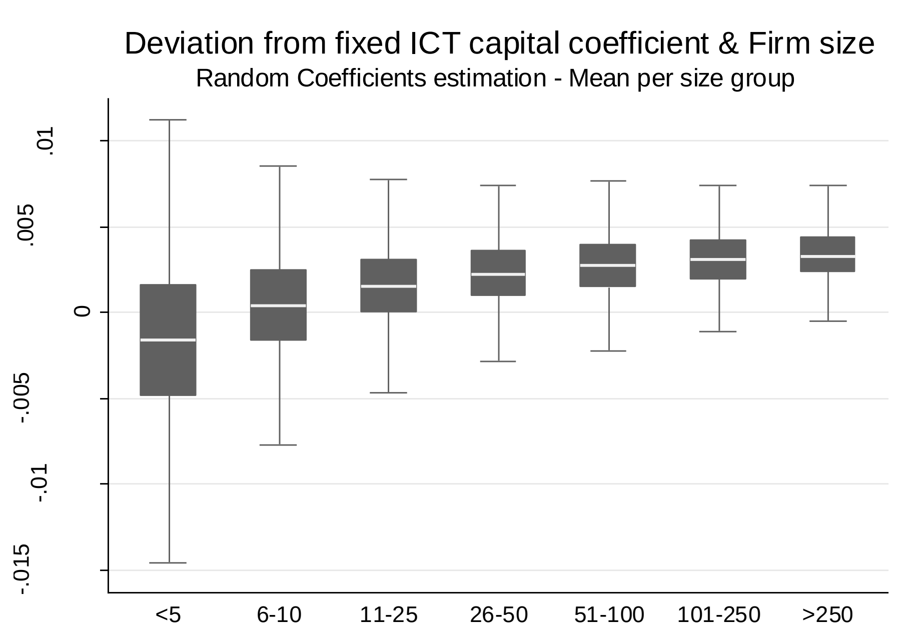


FIGURE A- 11: BOXPLOTS FIRM SPECIFIC ICT CAPITAL COEFFICIENTS PER FIRM SIZE BIN



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